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The Impact and Sustainability of Microfinance Institutions in Thailand

A thesis
submitted in partial fulfilment
of the requirements for the Degree
of Doctor of Philosophy

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by
Wittawat Hemtanon

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Abstract

The Impact and Sustainability of Microfinance Institutions in Thailand

by

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Income inequality is a major problem in Thailand. The Thailand Twelfth National Economic and Social Development Plan (12th NESDP), established in 2017 covering a five-year period, highlights the central role of microfinance institutions (MFIs) in enabling poor individuals and households to access financial resources at a reasonable cost. Though MFIs play an important role in alleviating poverty in developing countries, to date, there is no research simultaneously investigating the impact and sustainability of MFIs. Prior studies do not adequately address questions about MFIs' impact and sustainability. This study simultaneously evaluates MFIs' impact and sustainability in Thailand. The study uses a multinomial logit model, propensity score matching (PSM), a fixed effect model with PSM and financial performance indexes to evaluate MFIs' impact and sustainability. The study employs secondary data from Thailand's Socioeconomic Survey (cross-sectional data from 2017 and panel data from 2012 and 2017), to evaluate the accessibility and impact of selected MFIs. The study evaluates MFIs' sustainability using secondary data from the 2014 – 2016 annual Village Fund (VF) and Saving Groups for Production (SGPs) reports. These data were collected by the Government Savings Bank (GSB) through the 2017 MFI Competition.

The empirical results from the multinomial logit model reveal that the VF targets low-income rural households. The VF also encourages older individuals with lower education levels and female household heads to participate in their programme. Larger households are more likely to access the VF. Households with higher dependency ratios are less likely to borrow from the VF. This finding suggests that the VF cannot help less economically active households. Well-educated, young household heads in regional areas are more likely to borrow money from SGPs. SGPs' borrowers have higher household incomes than VF borrowers.

PSM and a fixed effect (FE) model with PSM were used to estimate the impact of the selected MFIs. The PSM results show that the impact of VFs is significant on income, education and transport expenditure but with negative signs. These results indicate that VFs do not improve borrowers' socio-

economic wellbeing. The empirical results reveal that SGPs' effects are significant for income but insignificant for expenditure. This indicates that SGPs borrowers effectively invest their loans in income-generating activities such as agricultural production and self-employment. The FE model with PSM results show that the VF increases education expenditure, but SGPs participation impacts income and transport expenditure. This indicates that SGPs improve borrowers' income and encourages them to increase investment in working capital and assets.

The results for MFIs' performance and sustainability show that both VFs and SGPs are profitable and financially sustainable. The determinants that affect Thai MFI sustainability are average loan balance per borrower, the number of borrowers per staff member, the total assets, the debt to equity ratio, the operating expense ratio, and the yield on gross loan portfolios.

Keywords: poverty, microfinance institutions' impact, microfinance institutions' sustainability, Village Funds, Saving Groups.

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Abbreviations

12 th NESDP	Thailand Twelfth National Economic and Social Development Plan
ADB	Asian Development Bank
BAAC	Bank of Agriculture and Agricultural Cooperatives
CAD	Cooperative Auditing Department
CDD	Community Development Department
CPD	Cooperatives Promotion Department
FSS	Financial Self-Sufficiency
GSB	Government Savings Bank
LR test	Likelihood Ratio test
MFI, MFIs	Microfinance Institution(s)
MLE	Maximum Likelihood Estimation
NESDB	Office of the National Economic and Social Development Board
NVFO	National Village and Urban Community Funds Office
PSM	Propensity Score Matching
ROA	Return on Assets
ROE	Return on Equity
SES	Socioeconomic Survey
SFD	Social Fund for Development
SFIs	Special Financial Institutions
SGP, SGPs	Saving Group(s) for Production
SMEs	Small and Medium-sized Enterprises
THB	Thai Baht
TDRI	Thailand Development Research Institution
VF, VFs	Village Fund(s)
WB	World Bank

Chapter 1

Introduction

1.1 Introduction

Over the past six decades, Thailand has been developing its economy based on national and social-development plans. These plans have encouraged economic growth by supporting the manufacturing industry, with the aim of increasing exports. As a result, the Thai economy has been one of the fastest growing economies in the world; GDP grew 10% per year in the 1990s (Warr, 2000). Between 1988 and 2017, the poverty rate dramatically declined from 65.17% of the population, or 34.2 million people, to 7.9 %, or 5.47 million people (ADB, 2019; NESDB, 2015; Warr, 2011).

However, income inequality remains a significant problem in Thailand. The Gini index shows that income inequality in Thailand is the highest in Southeast Asia (Bird et al., 2011). The index changes between 1988 and 2017 from 0.487 to 0.365, despite a declining poverty rate over the period (WB, 2019b). The lowest 10% of the Thai population had 3% share income whereas the highest 10% had 28.40% (WB, 2019a). Because of statistics like this, income inequality has become a national priority.

In a study on poverty, TDRI (2004) concludes that the major cause is low education. Because of low education levels, it is difficult for the poor to find jobs and improve their income. Even though half of the poor in Thailand reside in rural areas and work in the agricultural sector, most do not own land. A study by Bird et al. (2011) concludes that a key determinant of income inequality in Thailand is the lack of financial access to financial institutions for low-income families. Poor households cannot access formal financial institutions because of high transaction costs. The private sector is also reluctant to provide financial services to this group of clients (Bird et al., 2011). TDRI (2004) and Bird et al. (2011) suggest that microfinance programmes can assist in reducing income inequality. By providing small loans to individuals who typically do not have access to loans from formal financial institutions, they can invest in productive or income-generating activities. Understanding the poor and their background will enable the government and policy makers to develop more effective strategies, plans and policies to help alleviate poverty.

Thailand's 12th NESDP, established in 2017 to cover a five year period, shows the overall development vision linked to the vision of the 20-year national strategy (2017-2036). The document outlines the 20 year vision: "Thailand as a developed country with security, prosperity, and sustainability in accordance with the principles of the Sufficiency Economy Philosophy" (NESDB 2017, p. 5). The document states that this will be achieved through 10 core strategies.

- Strategy 1: Strategy of strengthening and realizing the potential of human capital
- Strategy 2: Strategy for creating a just society and reducing inequality
- Strategy 3: Strategy for strengthening the economy, and underpinning sustainable competitiveness
- Strategy 4: Strategy for environmentally-friendly growth for sustainable development
- Strategy 5: Strategy for reinforcing national security for the country's progress toward prosperity and sustainability
- Strategy 6: Strategy for public administration, corruption prevention, and good governance in Thai society
- Strategy 7: Strategy for advancing infrastructure and logistics
- Strategy 8: Strategy for the development of science, technology, research, and innovation
- Strategy 9: Strategy for regional, urban, and economic zone development
- Strategy 10: Strategy for international cooperation for development

Significantly for this study, two of the strategies relate to financial inclusion. The strategy for creating a just society and reducing inequality is designed to increase the productivity of the poorest sector of the population (set at 40%); the lowest income, the disadvantaged, women, and the elderly. This strategy also supports SMEs, community and social enterprises, the development of MFIs and greater financial access for job-creation. All of these activities are deemed important to achieve inequality alleviation.

The 12th NESDP strategy for strengthening the economy and underpinning sustainable competitiveness has one objective: to improve financial services access by creating a network of financial institutions (NESDB 2017, p. 107). MFIs enable poor individuals to access financial resources at a reasonable cost.

In Thailand, the main provider of microfinance programmes for poor households is the government, which has supported microfinance programmes for over 30 years (Bird et al., 2011; Fongthong & Suriya, 2014). Before the mid-1970s, informal lenders dominated the credit market in rural areas; informal lenders charge high interest rates that cause farmers to be in debt and in a vicious circle of poverty (Aditto, 2016). The Thai government has supported farmers since 1966 through the government agricultural bank that lends money to farming households (Siamwalla et. al., 1990). The

Thai government established and operates the BAAC that grants loans to agricultural households and cooperatives. The BAAC's primary aims are to provide loans with reasonable interest rates and so improve the clients' quality of life (Aditto, 2016; Menkhoff & Rungruxsirivorn, 2011). In 1975, the Bank of Thailand (BOT) sent a memorandum to all commercial banks requesting each bank to lend to agricultural households at least 5% of total of their loans (Siamwalla et. al., 1990). The Thai government successfully requested all commercial banks to increase agricultural loans and to offer these loans at low interest rates (Aditto, 2016; Yostrakul, 2018). This policy has enabled Thai rural households to participate in the formal credit system since the 1980s (Aditto, 2016; Yostrakul, 2018). Over 90% of rural households participated in some type of financial service (savings, loans from either formal or informal sources) (Bird et al., 2011). However, Thai rural households still rely heavily on informal credit sources (Yostrakul, 2018).

Many poor Thai households still depend on informal lenders because they lack collateral or have established patronage with informal lenders (Jitsuchon, 1989; Yostrakul, 2018). As Siamwalla et al. (1990) note, the poorest households cannot access formal rural finance because they present a high credit risk. The groups that benefit most from formal finance are middle-income households and the rich. As Bird et al. (2011) note, low-income Thai households have access to a limited range of financial services.

For the 12th NESDP strategy of creating a just society and reducing inequality and the strategy for strengthening the economy and underpinning sustainable competitiveness, MFIs play a vital role to help poor households access financial services. The following section provides an overview of Thai MFIs.

1.2 Microfinance Institutions (MFIs) in Thailand

MFIs in Thailand can be divided into three main groups (Bird et al., 2011). The first group covers formal MFIs, banks and nonbanking institutions that are controlled by prudential regulations. The MFIs in this group include commercial banks and SFIs. Two SFIs play an important role in providing financial access for low-income households: the BAAC and the Government Savings Bank (GSB) (Aditto, 2016). BAAC is a state-owned bank with a mission to grant loans to farmers and farmer associations in rural areas. BAAC also encourages farmers to save using a mobilization campaign for rural farmers. This product encourages rural households to increase their savings and develop greater financial responsibility. Similarly, GSB's core mission is to encourage Thai people to save. GSB grants loans to grassroots clients through the GSB loan projects, e.g., the People Bank Loan and the Rural Community Development Loan.

The second group consists of semi-formal MFIs that are not controlled by prudential regulations. However, they still have legal status (Tambunlertchai, 2015). The second group includes cooperatives, Saving Groups for Production (SGPs) and Village Funds (VFs). Cooperatives consist of a group of individuals with the same occupation and/or live in the same area. Members pool their resources to help each other (Tambunlertchai, 2015). Cooperatives offer members deposit and credit services. The primary aim of cooperatives is to improve the members' quality of life (Aditto, 2016). Members purchase shares in the cooperatives. Thai cooperatives have exhibited significant growth in terms of members, increasing from 10,329,036 persons in 2009 to 11,636,166 in 2018 (CPD 2019). These institutions operate under the Cooperative Act 1968 and are supervised by the CPD and CAD (Aditto, 2016). SGPs have two important aims: to develop sustainable human capital and solve members' lack of credit access in rural areas (Aditto, 2016). SGPs are member-based rural community financial institutions established with the support of the CDD of the Ministry of Interior (MOI) (Tambunlertchai, 2015). VFs were introduced to the Thai rural financial system by the Thai government in 2001; VFs are community-based. The programme operates under the supervision of the NVFO. The NVFO is responsible for developing and implementing various policies, rules and regulations (Aditto, 2016; Tambunlertchai, 2015).

The third group covers informal MFIs that are not established or covered by government legislation. This group is smaller than the formal and semi-formal groups. They are often savings groups run at a village level (Bird et al., 2011; Tambunlertchai, 2015). Such savings groups are typically founded by community members who establish the groups to save, provide welfare benefits and lend money to members. After saving money for a defined period (it varies between groups), members can borrow from the group funds for hospitalization, funeral or educational expenses. Funds can also be used for community development. These groups are informal, so it is difficult to track the total members and the total amount of members' funds (Meagher, 2013).

Studies have shown that, in Thailand, most low income and poor people can access financial services from community-based MFIs, such as VFs, cooperatives, and SGPs (Microfinance Services Ltd., 2013; Tambunlertchai, 2015). Microfinance Services Ltd. (2013) reveals that over 50% of VF borrowers and 40% of SGPs borrowers have average incomes of less than THB 6,000 per month. Therefore, these Thai MFIs are important in encouraging the poor to participate in financial services, which can ultimately help them escape poverty. This study focuses on VFs and SGPs.

Village Funds (VFs)

The VF programme, the largest government microfinance programme in Thailand, was launched by the government in 2001. The Thai government provided THB 1 million (about USD 22,500 at a 2001 average exchange rate of USD 1 = THB 44.5) per village to over 77,000 villages and urban

communities across the country (Fongthong & Suriya, 2014). After the general election in 2011, the government increased funding to this programme to THB 2 million (about USD 65,800 at a 2011 average exchange rate of USD 1 = THB 30.4) per village. This programme is important in the credit market in Thailand, especially for the poor who live in rural areas and are often unable to access formal financial services (Fongthong & Suriya, 2014).

The VF has four official objectives (The National Village and Urban Community Fund Act, 2003). First, the programme provides loans for investment, job creation, income generation, welfare improvement and expense reduction. Secondly, it provides emergency funds, a form of non-productive credit. These loans are small and have maturity dates of less than one year. Thirdly, it may supply loans to other VFs for economic and social strengthening. This programme aims to develop the rural economy.

The National Village and Urban Community Fund Act established the VFs' guidelines. People cannot borrow up to THB 30,000. In some cases, loans were extended to THB 75,000 if borrowers met a higher standard of creditworthiness. Emergency loans are limited to THB 15,000. The interest rate must not exceed 15% per year. A borrower must have two guarantors and repay the loan within two years.

The VF is administered at two levels: nationally and at the village level. The National Committee of the Central Government oversees VFs at the national level. There are 76 provincial and 928 district sub-committees. The village level committees have 9-15 members elected from villagers who have lived in the village for at least two years. At least half of the committee members must be women. The committees set the rules and manage the funds. The local committees also decide which loans to grant and how much money is lent to borrowers (Fongthong & Suriya, 2014).

Saving Groups for Production (SGPs)

SGPs were established in 1974 by community leaders to encourage members to save. The SGPs' idea is to gather people of different status in a village to help each other solve their investment problems (Luxchaigul, 2014). The local people regularly save money in a cash pool. Saving is the best way for funds' accumulation (Luxchaigul, 2014). SGPs' economic activities begin with saving for welfare provision and loans. Borrowers obtain loans to invest in their businesses (Luxchaigul, 2014). SGPs also provide loans to improve members' lives and to deal with emergencies. Borrowers must have four guarantors and pay a maximum interest rate of 15%. SGPs play an important role in providing microfinance services to the poor (Meagher, 2013). SGPs can create rural financial markets using a bottom-up approach (Akihiko, 2015).

SGPs as community-based financial institutions have been established in all Thailand's regions. SGPs are supported by the CDD of the MOI. CDD sets the loan guidelines and evaluates SGPs' reports. SGPs are not controlled by prudential regulations but are assessed by CDD via financial institution indicators. In 2012, there were 26,819 SGPs, with 3.6 million members and THB 36.9 billion in savings. The repayment rate is high, approximately 99% (Meagher, 2013).

1.3 Research Problem

MFIs are important in alleviating poverty in developing countries. Policymakers are interested in the role of microfinance programmes but there are no studies that have evaluated the impact and sustainability of MFIs in the same study. The studies answered two questions:

- (1) Does microfinance impact on the borrower's social and economic welfare?
- (2) Is the microfinance institution sustainable?

The first answer can be used to develop microfinance programmes as an instrument to alleviate poverty. The second answer should show strong evidence of the determinants that affect MFIs' sustainability. There is no research that simultaneously investigates both the impact and sustainability of MFIs. Hermes, Lensink and Meesters (2008) conclude that many questions about MFIs' impact and sustainability are not adequately answered.

1.4 Research Questions

The aim of this study is to simultaneously evaluate MFIs impact and sustainability in Thailand. The research questions are:

- (1) What are the determinants of households' credit participation in microfinance programmes in Thailand?
- (2) How do microfinance programmes affect the economic and social welfare of households in Thailand?
- (3) How well do MFIs in Thailand perform?
- (4) What are the determinants that impact the sustainability of MFIs in Thailand?

1.5 Research Objectives

The first objective explores the determinants of households' credit participation in Thailand. There are many studies on this issue, but no specific study has addressed the factors that impact credit participation in Thailand at the village level. This can be done by comparing the determinants of

credit participation of VFs and SGPs. A VF is a microfinance programme established by the government whereas SGPs are semi-formal MFIs established by village leaders. Fongthong and Suriya (2014) investigate only the determinants of borrowers from the VF. Menkhoff and Rungruxsirivorn (2011) find that VF can improve access to finance for the poor compared with other financial institutions. Therefore, it is important to develop microfinance programmes that are targeted specifically at the poor.

The second objective is to investigate the impact of microfinance programmes on the economic and social welfare of households in Thailand. It is important to understand the impact of microfinance programmes because the results are crucial towards developing effective microfinance products and services that can help reduce poverty problems (Cintina & Love, 2014; Hermes & Meesters, 2011).

Some studies have focussed on the impact of microfinance programmes in Thailand, especially at the village level. Kaboski and Townsend (2012) and Boonperm, Haughton and Khandker (2013) investigated VFs' impact on rural households' economic welfare. There are no studies that examine the VFs impact on households at both at an economic and social welfare level. Only Coleman (1999) examines the impact of village banks in northeast Thailand on both economic and social welfare. Coleman (1999) uses a quasi-experimental design to measure the impact and finds that there is an insignificant impact on a set of outcomes such as savings, expenditure and physical assets. However, there is a significant negative impact on expenditure on men's health care and a significant positive impact on women's high-interest debt.

The third objective evaluates VFs' and SGPs' financial performance to determine how well MFIs are doing financially and how to improve the institutions' future performances. This objective's result benefits MFIs internal management (Ledgerwood, 1998). Ledgerwood (1998) presents six indicators to evaluate MFIs' financial performance and outreach. These indicators are usually in the form of financial ratios that compare MFIs' performance over time and are analysed by trend analysis. For example, Agarwal and Sinha (2010), Arthur et al. (2013), and Bhuiyan et al. (2011) examine the financial performance of MFIs. Agarwal and Sinha (2010) analyse MFIs' financial performance in India using six parameters of financial performance: financial structure, revenue, expense, efficiency, productivity and risk. The study finds that MFIs that performed well in India use a business model. Bhuiyan et al. (2011) compare the performance of MFIs in Malaysia and Bangladesh in terms of institutional characteristics, financial structure, outreach indicators, overall financial performance (sustainability), expenses, efficiency, and productivity. They show that MFIs' performance in Malaysia is better than in Bangladesh in terms of operational self-sufficiency, earnings and expenses. However, performance is lower in terms of outreach and efficiency. Arthur et al. (2013) evaluate MFIs' performance using financial performance indicators such as financial sustainability, profitability

and market share, and portfolio management, like Ledgerwood (1998). They find that MFIs' financial performance in Uganda is strong and profitable. However, they also recommend that these MFIs should enhance their financial reporting framework to improve their liquidity, asset values, market share, financial sustainability and portfolio quality. Study of MFIs in Thailand is limited (Eur-U-Sa, 2011). Eur-U-Sa (2011) investigates BAAC's performance and outreach. The author determines the relationship between outreach and financial performance using secondary data from BAAC annual reports from 2004 to 2009 and finds that the breadth of outreach indicators have complementary relationships with financial performance and financial sustainability.

The fourth objective investigates the determinants that affect MFIs' sustainability. Scholars are concerned about the sustainability of MFIs. Schreiner (2000) suggests that MFIs might help poor people but, in the future, they will not be able to help the poor because the institutions must achieve a good financial performance to be sustainable. Kinde (2012) argues that financial sustainability is the major condition for MFIs' sustainability in Ethiopia. The author finds that MFI sustainability is affected by the breadth and depth of outreach, the dependency ratio and the cost per borrower.

Some MFIs in Thailand are government-funded. These institutions do not focus on profit-making (Hermes & Lensink, 2011). Individuals who obtain loans from these government-funded MFIs believe that these programmes will always be publicly, financially supported. Thus, they do not actively commit themselves to paying back the loans (Armendariz de Aghion & Morduch, 2004). This results in moral hazard behaviour and damages MFIs' long term sustainability in Thailand.

Unlike other countries, many Thai MFIs were established by groups of individuals (often living in the same community or village) on a voluntary basis. These include Savings Groups and Sajja Savings groups. These MFIs are funded and managed by community leaders and these MFIs' survival appears to depend entirely on their leaders. If the leaders cannot maintain their position in the community or they are no longer involved in the MFI, these MFIs may not survive (TDRI, 2004). The MFI sustainability results are important for policymakers. Moreover, the results can be used to improve MFIs' productivity, reduce donor funds, decrease operational costs and generate financial revenue (Rahman & Mazlan, 2014).

1.6 Significance of the Study

This study contribute to the development of the microfinance sector in Thailand. Studies have shown that in Thailand, most low income and poor households can access financial services from community-based MFIs, such as VFs and SGPs (Microfinance Services Ltd., 2013; Tambunlertchai, 2015). However, no study has evaluated the impacts and sustainability of community-based Thai MFIs simultaneously. This study focuses on the Village Funds and Saving Groups for Production.

While VF microfinance programmes are established by the government, SGPs are semi-formal MFIs established by village leaders. It is important to understand the impacts and sustainability of VFs and SGPs simultaneously because these results will provide a better landscape of MFIs in Thailand.

Furthermore, understanding the impact and sustainability of MFIs will help policymakers create appropriate policies on microfinance products and services and MFI performance. Developing effective microfinance products and services will help reduce the country's poverty. In addition, policymakers can use the study's results to improve MFIs productivity, reduce donor funds, decrease operational costs and generate financial revenue.

This study found that VFs and SGPs are major credit sources in Thailand rural credit market. These programmes enable low-income households to access multiple sources of credit which ultimately leads to high levels of debts. The government should provide training courses on financial management and financial literacy to help households struggling with financial issues. In terms of MFI sustainability, this study found that both VFs and SGPs are sustainable. MFI sustainability is affected by staff member productivity and operating expenses. The government should encourage MFIs to use advanced technology to minimise their transaction costs and should create legislation that can help MFIs access long-term debt to improve their performance.

1.7 Data and Data Analysis Methods

1.7.1 Data Collection

This study uses cross-sectional data (2017) and panel data from the Socioeconomic Survey (SES) (2012 and 2017) to evaluate the accessibility and impact of VFs and SGPs on Thai households. Cross-sectional data are from the SES Survey (2017) collected by the National Statistical Office of the Ministry of Information and Communication Technology. The Office interviewed 43,210 households (both borrowers and non-borrowers) across the country. Data were collected monthly. The information includes a variety of household socioeconomic data, including household income, expenses, assets, and liabilities.

Panel data from the SES surveys in 2012 and 2017, were collected by the National Statistical Office of the Ministry of Information and Communication Technology. In the 2017 survey, 4,461 households across the country were sampled. Data were collected monthly. The information includes a variety of household socioeconomic data, such as household income, expenses, assets, and liabilities. The 2012 survey used the same questionnaire but covered 6,080 households. The sample used in this study includes 4,406 households (both borrowers and non-borrowers) from across the country.

To evaluate VFs' and SGPs' performance, secondary data were collected from the annual reports from 2014 to 2016. The annual reports include general VFs and SGPs information and financial statements. The annual reports provide information about the number of members, the number of active borrowers, the total value of loans, the revenue, expenses, profits and losses, assets, liabilities and equities. This study uses the annual VFs and SGPs reports from 2014 to 2016 to achieve objectives 3 and 4.

1.7.2 Scope of the Study

This present study focuses on semi-formal MFIs at the village level in Thailand because most low income, poor people in Thailand can access financial services from community-based MFIs, such as VFs, cooperatives and saving groups (Microfinance Services Ltd., 2013; Tambunlertchai, 2015). In Thailand, semi-formal MFIs play an important role in providing financial services to the poor. Such financial services can help them escape poverty. This study focuses on the VFs and SGPs. VFs are supported by the GSB. The GSB is a government bank that finances VFs. SGPs are supported by the CDD. The CDD is a government department that supports SGPs in all Thailand's districts.

1.7.3 Methods and Estimation Procedures

Four main methods are used to answer this study's research questions. First, the multinomial logit model is used to determine household characteristics that affect participation in microfinance programmes. Secondly, Propensity Score Matching (PSM) and the fixed effect model are used to examine the impact of microfinance programmes. These methods can be used to resolve selection bias problems (Carreras, 2012). Thirdly, the study examines MFIs' performance using financial ratios analysis techniques. These ratios explain financial structure and financial performance. Finally, the panel regression technique, which involves pooling observations on a cross-section of units over several time periods, is used to investigate the determinants that affect MFIs' sustainability. This study uses panel regression because this model can address a broader range of issues and tackle more complex problems (Kinde, 2012). Panel data combine cross-sectional data and time series data. This technique can increase the degrees of freedom and, therefore, the power of the test (Kinde, 2012). The model is used to solve multicollinearity problems among the independent variables that can arise if one uses a time series model alone (Kinde, 2012).

1.8 Structure of the Thesis

The rest of the thesis is organized into six chapters. Chapter 2 presents an overview of literature on the determinants of microfinance participation, the impact of microfinance on economic and social welfare, and MFIs' performance and sustainability. Chapter 3 describes the research methodology and data collection methods. The results are discussed over two chapters. Chapter 4 focuses on the

determinants that affect household participation in microfinance programmes. This chapter also evaluates VFs' and SGPs' impact on economic and social welfare. Chapter 5 assesses VFs' and SGPs' performance and investigates the factors that affect MFIs' sustainability. Finally, Chapter 6 summarizes the research findings, discusses the study's limitations, provides policy recommendations and suggests future directions for research.

Chapter 2

Literature Review

This chapter addresses four areas of microfinance literature and is divided into six sections. Section 2.1 reviews the literature on credit markets and the problem of asymmetric information, the theory of credit rationing and the household demand for credit in credit markets. Section 2.2 summarizes the literature on microfinance participation, including the determinants of and models for participation in microfinance programmes. Section 2.3 discusses the impact of microfinance evaluation, including the impact evaluation methodologies. Section 2.4 analyses MFIs' performance, including performance proxies. Section 2.5 reviews the MFIs' sustainability, including the determinants and models for sustainability. Finally, section 2.6 summarizes the chapter.

2.1 Credit Markets and the Problem of Asymmetric Information; Credit Rationing and Household Demand for Credit in Credit Markets

2.1.1 Credit Markets and the Problem of Asymmetric Information

The market for lemons, or a market with asymmetric information characteristics, leads to market failure (Akerlof, 1970). Akerlof's (1970) study on the market for lemons shows that one side of the transaction has more information than the other. The market for lemons symbolizes the theory of asymmetric information. Applied to the credit market, this theory suggests that borrowers know more than lenders about the probability of success of their projects or investments. In short, lenders cannot differentiate between safe and risky borrowers because they do not have enough information. Asymmetric information flow leads to problems of adverse selection and moral hazard (Mishkin, 2004). These issues are key concerns for any lenders.

The adverse selection problem arises because borrowers withhold vital information (Quach, 2005; Stiglitz & Weiss, 1981). This problem occurs during screening, which involves differentiating between safe and risky borrowers. In screening, lenders need to differentiate between good and bad borrowers; lenders do not know the probability of success of the borrowers' projects or investments. Lenders may reject safe applicants but grant loans to risky applicants (the adverse selection effect) (Quach, 2005; Stiglitz & Weiss, 1981). In this process, the transaction cost involves differentiating borrowers using the borrowing costs or the interest rate. If lenders increase interest rates to compensate for high transaction costs, this increase may eliminate good borrowers from the pool of potential borrowers. Hence, only risky borrowers remain (Quach, 2005; Phan, 2012).

The moral hazard occurs when lenders grant loans to borrowers. In turn, borrowers may alter their projects or investments, which alters the probability of repayment. Thus borrowers alter the lenders' expected returns (the moral hazard effect) (Quach, 2005; Stiglitz & Weiss, 1981). The moral hazard relates to monitoring and enforcement mechanisms, where borrowers decide not to repay their loans because they know that the lenders share part of the risk (Pham & Lensink, 2007). If the loan contract cannot enforce borrowers to repay loans, borrowers may refuse to pay back their loans. Moral hazard theory assumes that borrowers intend to repay loans when they have the means to do so (Ghosh, Mookherjee & Ray, 2000).

Lenders not only decide to whom to grant credit but also how much, based on the information that they obtain from borrowers. However, asymmetric information discourages lenders from granting loans to all applicants or asymmetric information induces lenders to grant loans to risky borrowers. In short, lenders invest in risky projects (Quach, 2005; Stiglitz & Weiss, 1981). This is known as credit rationing and leads to credit constraints for borrowers, regardless of their individual repayment capability (Armendariz de Aghion & Morduch, 2005).

2.1.2 Credit Rationing

Stiglitz and Weiss (1981) state that there are two underlying assumptions underpinning credit rationing. First, banks (or lenders) cannot differentiate between safe and risky borrowers. Second, lenders cannot enforce loan repayments. For example, if an investment's or project's returns are less than the debt obligations, borrowers may choose not to repay (regardless of their returns, i.e., they have enough money to do so) by realizing that the bank cannot enforce the contract. This is the problem of contract enforcement (Ghosh et al., 2000).

A Model of Credit Rationing

A simple ex-ante asymmetric information model is used to illustrate how credit rationing happens in credit markets. This model assumes that there are two agents in the credit market; households and lenders. Each household is assumed to be a borrower. The borrower has an opportunity to invest in a project to generate income but lacks capital. This model also assumes that the borrower's initial wealth is only in the form of labour which they trade in the labour market. The borrower, therefore, looks for credit facilities. The lender grants loans with the expectation of making a profit. This model assumes that the credit market is characterised by asymmetric information (Quach, 2005; Stiglitz & Weiss, 1981).

This study follows Stiglitz and Weiss' (1981) assumption that projects or investments have an expected return (μ_i), but different probabilities of success (ρ_i). A borrower's decision is based on a risk-averse attitude. The return on projects or investments consists of a project either succeeding or

failing, (μ_i^S) and (μ_i^f) , respectively. The lender offers the same contract with an interest rate (r) and a loan (B) to all borrowers, with the same expected project or investment return.

The return of successful projects is assumed to be greater than $(1+r)B$, which is the repayment to the lender. The return of a failed project is assumed to be lower than $(1+r)B$. A project or investment is launched if the expected return, in the case of success, is greater than the opportunity cost, W , which is the initial wealth of the individual borrower. Therefore, the expected project return for an individual borrower can be illustrated as (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981):

$$\mu_i = \rho_i \mu_i^S + (1 - \rho_i) \mu_i^f \quad (2.1)$$

$$\pi(\rho_i, r) = \rho_i [\mu_i^S - (1 + r)B] \geq W_i \quad (2.2)$$

Adding equation (2.1) to equation (2.2), we obtain (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981):

$$\pi(\rho_i, r) = \mu_i - \mu_i^f + \rho_i [\mu_i^f - (1 + r)B] \geq W_i \quad (2.3)$$

Differentiating equation (2.3), with respect to ρ_i , we get (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981):

$$\frac{\partial \pi(\rho_i, r)}{\partial \rho_i} = \mu_i^f - (1 + r)B < 0 \quad (2.4)$$

In the case of failure (μ_i^f) , the expected return is less than the expected return in the case of success (μ_i^S) , and the repayment to the lender $(1 + r)B$. Equation (2.4) implies that the expected return to the borrower is a decreasing function of the probability of success ρ_i . Therefore, at a certain interest rate, the least risky projects or investments have a lower break-even point and the riskiest projects or investments have a higher break-even point (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981).

Considering the relationship between the interest rate and the probability of success, differentiating r with respect to ρ_i in equation (2.4), using the implicit function theorem, we obtain (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981):

$$\frac{\partial r}{\partial \rho_i} = - \frac{\partial \pi(\rho_i, r) / \partial \rho_i}{\partial \pi(\rho_i, r) / \partial r} < 0 \quad (2.5)$$

Equation (2.5) shows that $\partial \pi(\rho_i, r) / \partial \rho_i < 0$ and $\partial \pi(\rho_i, r) / \partial r < 0$. The equation implies that an increase in the interest rate (charged by the lender) leads to a decrease in the probability of success of a project or investment. This means that if a lender increases the interest rate, marginal borrowers may withdraw and, thus, only risky borrowers remain in the credit market. In short, borrowers seek projects or investments that provide higher returns but have lower success rates. This effect is

documented in Keeton's (1979) and Stiglitz and Weiss' (1981) studies. This idea is presented in Figure 2.1.

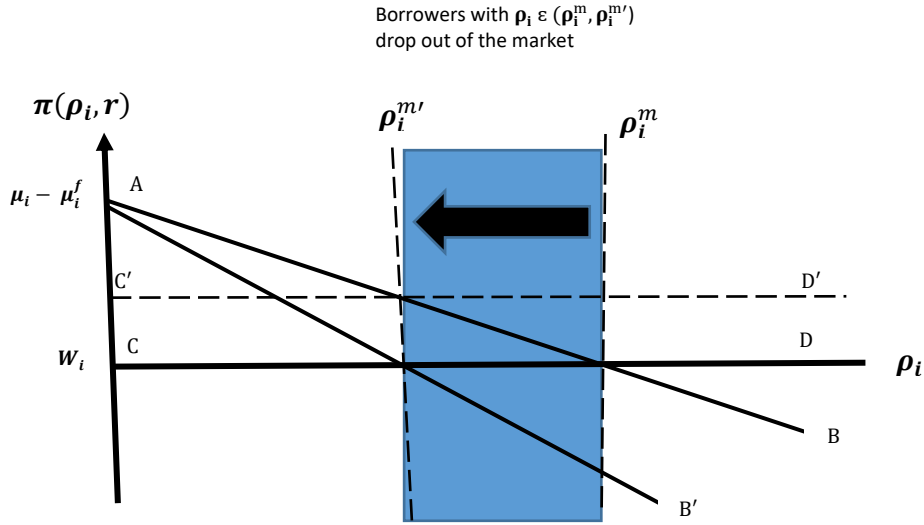


Figure 2.1 The Expected Returns for Borrowers and the Probability of Success.

Source: Adapted from Quach (2005)

Figure 2.1 illustrates the effect of a change in interest rate on a borrower's expected return and the effect of an increase in opportunity costs. The line A-B in equation (2.3) depicts a borrower's expected return when the probability of success varies; ρ_i^m shows the probability of success for marginal borrowers. Failed projects exhibit negative returns, as shown in equation (2.4), $\mu_i^f - (1+r)B < 0$, thus, if the interest rate (r) is increased, borrowers' expected returns will move from A-B to A-B'. Marginal borrowers' expected returns are lower than their opportunity costs. Therefore, marginal borrowers drop out of the credit market. New marginal borrowers now confront the probability of success, $\rho_i^{m'}$, which is lower than ρ_i^m . This implies that there are more risky borrowers in the pool. In the same way, if the opportunity cost increases from C-D to C'-D', the result is the same effect (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981).

The lender always expects to receive full repayment $(1+r)B$ with a successful project and receive μ_i^f for a failed project. The expected return to the lender can be written as follows (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981):

$$\kappa(\rho_i, r) = \rho_i(1+r)B + (1-\rho_i)\mu_i^f = \rho_i[(1+r)B - \mu_i^f] + \mu_i^f \quad (2.6)$$

Differentiating equation (2.6) with respect to ρ_i , (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981):

$$\frac{\partial \kappa(\rho_i, r)}{\partial \rho_i} = (1+r)B - \mu_i^f \quad (2.7)$$

The term $(1 + r)B - \mu_i^f > 0$, in equation (2.7) implies that the expected bank returns are a function of the probability of the success of a programme or investment. Interest rates affect the lender in two ways. First, an increased interest rate leads to an increase in $(1 + r)B - \mu_i^f$. In short, an increased interest rate refers to an increase in interest income. Secondly, increasing interest rates leads to a decrease in ρ_i . As equation (2.5) shows, when the interest rate increases, lenders receive a lower expected return because lower-risk borrowers drop out of the credit market (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981).

Hence, there is a critical equilibrium interest rate (r^{ra}) where, if the interest rate r is lower than the equilibrium interest rate (r^{ra}), the lender can increase interest rates. This practice does not affect lower-risk borrowers or cause them to drop out of the credit market (Stiglitz & Weiss, 1981). As a result, lenders' expected return increases. If the interest rate increases beyond the equilibrium interest rate (r^{ra}), low risk borrowers drop out, leading to increased numbers of risky borrowers in the credit market. As a result, lenders' expected return decreases. Lenders then prefer to allocate credit at r^{ra} . However, this leads to the problem of underinvestment (Phan, 2012; Quach, 2005; Stiglitz & Weiss, 1981).

Figure 2.2 shows the relationship between the lenders' expected returns and credit rationing, based on demand and supply curves, and the credit market interest rate. The upper right part of Figure 2.2 illustrates the critical interest rate, r^{ra} , which is a lender's highest expected return. Therefore, if at r^i , the loan supply equals the loan demand, no credit rationing occurs. In fact, at this point, the demand for credit is higher than the loan supply. Stiglitz and Weiss (1981) state that it is better for lenders to ration credit (rather than increase the interest rate) to solve excess demand for credit because, if the interest rate increases, low risk borrowers drop out leading to an increased number of risky borrowers in the credit market. As a result, lenders' expected return decreases.

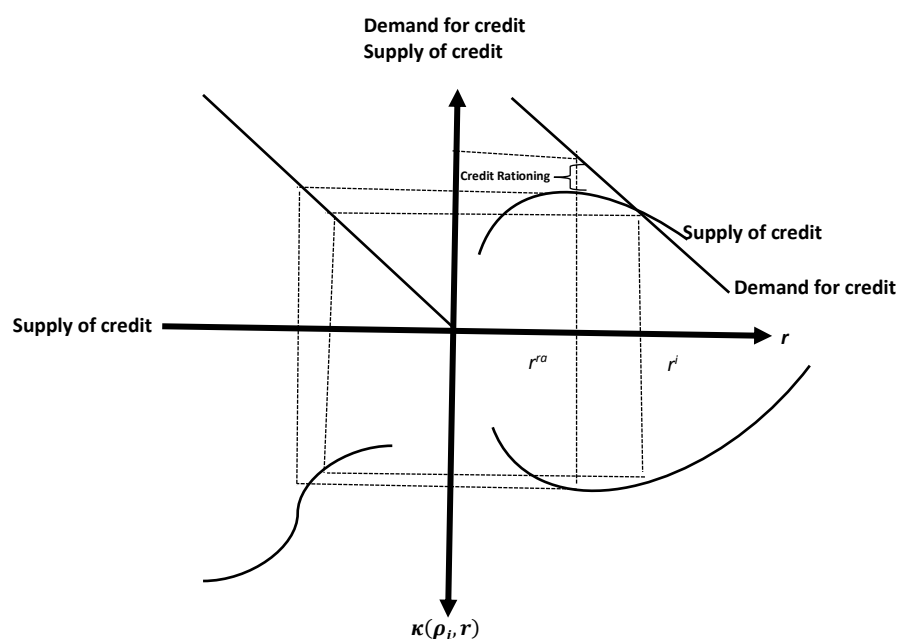


Figure 2.2 Lender Returns and Credit Rationing

Source: Adapted from Stiglitz and Weiss (1981)

There are two types of credit rationing; internal credit rationing and external credit rationing (Phan, 2012). The first is associated with the demand for credit. It refers to a borrower's acts of self-rationing (asking for the smallest possible loan). In other words, borrowers assess the risks themselves. Internal credit rationing is a function of a borrower's risk aversion, business and finance risk levels, and a project's specific forms of risk management (Barry et al., 1995). The perceived risks may change over time because of changes in assets, experience and household characteristics (Barry et al., 1995).

The second, external credit rationing, is related to the supply side of credit and refers to lenders' decisions about whether to grant the total amount requested by borrowers (Barry et al., 1995). Lenders use creditworthiness criteria to determine whether to grant the full amount. Collateral can reveal a borrower's creditworthiness and lenders ask for collateral to overcome problems associated with adverse selection with ex-ante loan contracts (Stiglitz & Weiss, 1981). In short, collateral reduces external rationing levels. There are loan contracts with different levels of credit rationing: complete, part, or no credit rationing. In other words, because of their lack of collateral, loan applicants are offered credit based on their collateral.

External credit rationing is also influenced by the lender's characteristics, the lender's legal structure and the regulatory environment operating (Barry et al., 1995). Credit constraints can be decreased by reducing the lender's transaction costs. In other words, credit participation can be improved by enhancing investment in physical infrastructure (roads, bridges, public transports and communication, in rural areas) and institutional infrastructure before launching financial services in

the credit market (Phan, 2012). Generally, external credit rationing is described as credit constraint in various economic models. The next section discusses the use of external credit rationing as one form of credit constraint on household credit demand. The theory explains credit participation in this study.

2.1.3 Household Demand for Credit

This study derives the household demand for credit. We assume that households desire to maximize their satisfaction levels via consumption under the underinvestment of credit rationing as discussed above. Household consumption can be explained using the standard Ramsey model (Phan, 2012).

This model shows that the i^{th} household chooses a stochastic consumption plan to maximize the expected value of the lifetime utility function. This study also demonstrates that borrowing increases a household's consumption over time via increasing output under credit constraints.

A household's production function consists of labour (L) and own capital (K). This function assumes a constant return to scale. Following credit constraint, it leads to diminishing returns on private capital. Private capital cannot be mobilized perfectly between households. The general production function is (Phan, 2012; Turnovsky & García-Peñalosa, 2008):

$$Y = F(K, L) \quad (2.8)$$

Where: Y is Output; K is Capital and L is Labour.

Following the assumption of a constant return to scale, this study uses the intensive form of the production function (Romer, 2001). Setting constant $\frac{1}{L}$ in equation (2.8), the production function can be expressed as (Romer, 2001):

$$Y = F(K/L, L/L)$$

$$Y = F\left(\frac{K}{L}, 1\right) = \frac{1}{L} F(K, L) \quad (2.9)$$

where $\frac{K}{L}$ is the amount of capital per unit of labour and $\frac{1}{L} F(K, L)$ is $\frac{Y}{L}$, the output per unit of labour.

Defining $k = \frac{K}{L}$, $y = \frac{Y}{L}$, we can rewrite equation (2.9) in per capita terms as the average product of capital (Phan, 2012; Romer, 2001):

$$AP_k = y = \phi(k) \quad (2.10)$$

The production function in per capita terms is the marginal product of capital (Phan, 2012; Romer, 2001):

$$MP_k = y' = \phi'(k) \quad (2.11)$$

Equation (2.11) possesses the following properties (Phan, 2012; Romer, 2001):

$$\phi'(k) > 0 \text{ and } \phi''(k) < 0 \text{ for all } k > 0 \quad (2.12)$$

$$\text{And } \lim_{k \rightarrow \infty} \phi'(k) = 0 \text{ and } \lim_{k \rightarrow 0} \phi'(k) = \infty$$

Assuming the total output is divided between consumption (C) and gross investment, (I_g) can be shown as Equation (2.13a) (Phan, 2012; Romer, 2001):

$$Y = C + I_g \quad (2.13a)$$

If depreciation (δ) is considered, net investment (I) can be expressed as (Phan, 2012; Romer, 2001):

$$I = \dot{K} = I_g - \delta K \quad (2.13b)$$

Adding equation (2.13a) into equation (2.13b), we obtain:

$$I = \dot{K} = I_g - \delta K = Y - C - \delta K \quad (2.13c)$$

Substituting per the capita term into equation (2.13c), it can be seen that (Phan, 2012; Romer, 2001):

$$\dot{k} = \phi(k) - c - (n + \delta)k \text{ where } c \equiv \frac{C}{L} \text{ and } n \equiv \frac{dL/dt}{L} \quad (2.14)$$

Equation (2.14) shows how the capital-labour ratio (\dot{k}) varies over time. This equation also describes the relationship between the capital-labour ratio (\dot{k}) and the population growth rate (n), the depreciation rate (δ), and per capita consumption (c) at the household level.

The level of per-capita consumption determines household utility and welfare at any one time.

Therefore, household utility, $U(c)$, can be written as (Phan, 2012; Romer, 2001):

$$U(c) = \frac{c^{1-\sigma}}{1-\sigma} \quad (0 < \sigma < 1) \quad (2.15)$$

Equation (2.15) shows that the household utility function ($U(c)$) is increasing and concave in relation to per capita consumption (c). The properties in this function can be shown as (Phan, 2012; Romer, 2001):

$$U'(c) = C_{(t)}^{-\sigma} > 0 \text{ and } U''(c) = -\sigma C_{(t)}^{-(1+\sigma)} < 0 \text{ for all } c > 0 \quad (2.16)$$

$$\text{and } \lim_{c \rightarrow \infty} U'(c) = 0 \text{ and } \lim_{c \rightarrow 0} U'(c) = \infty$$

Our study assumes that individual households maximize inter-temporal additive utilities integral to the standard Ramsey model. Using the integrating process to attain utility maximization at any one time, utility maximization should consider population growth (n), and the discount rate (ρ) (Phan, 2012; Romer, 2001). Total utility measures the instantaneous average per capita utility, which depends only on per capita consumption at a discount rate (ρ) at any one period (t). If the discount rate (ρ), and the subjective rate of time preference (σ) are higher, the contribution of a future generation's utility is lower (Phan, 2012; Romer, 2001). A higher rate of time preference means that a household prefers to maintain current consumption levels under capital constraints.

If the rate of return to savings (r) is different from the discount rate (ρ) and the population growth rate (n), the inter-temporal additive utility function in reduced form is (Phan, 2012; Romer, 2001):

$$\int_0^{\infty} \frac{C_t^{1-\sigma}}{1-\sigma} e^{-(\rho-n)t} dt \text{ where } (r \equiv \rho - n > 0) \quad (2.17)$$

Equations (2.17) and (2.14), and the set of assumptions outlined above, form the standard optimal consumption growth. Using the dynamic optimization method, the derivation of the optimal rate of household consumption satisfies the Euler equation (Phan, 2012; Romer, 2001):

$$\dot{c} = \frac{U'(c)}{U''(c)} [\phi'(k) - (n + \delta + r)] \quad (2.18)$$

The optimal rate of consumption is (Phan, 2012; Romer, 2001):

$$g(t) \equiv \frac{dC_t/C}{dt} \quad (2.19)$$

The rate of depreciation plus the labour augmenting technical progress can be written as (Phan, 2012; Romer, 2001):

$$d = \delta + n \quad (2.20)$$

The relationship between the rate of consumption growth, $g(t)$ and the marginal product of capital, $MP_k = y' = \phi'(k)$, is (Phan, 2012; Romer, 2001):

$$g(t) \equiv d \ln C_t = \frac{1}{\sigma} [MP_k - (n + \delta + r)] = \frac{1}{\sigma} [MP_k - (d + r)] \quad (2.21)$$

In equation (2.21), the rate of consumption growth, $g(t)$, depends on the marginal product of capital, $y'(k)$, the subjective rate of preference, ρ , the depreciation rate, d , and the inter-temporal elasticity of substitution, σ . However, only MP_k and d are induced by external capital. In the other words, under credit rationing and credit constraint conditions, a household's demand for credit can improve an individual's utility by increasing the marginal product of capital, MP_k . The marginal

product of capital can improve via the production cycle or directly finance some basic needs, via reducing constraints of current obligations in terms of the depreciation rate (Phan, 2012).

There are two examples that show utility improvement by increasing the marginal products of capital and decreasing credit constraints. One can use the agricultural sector to explain utility improvements by increasing the marginal products of capital. Farmers spend a lot of money on seeds and fertilizers. However, the production may take weeks or months to generate income and many rural poor households do not have enough money to invest. Therefore, these households need to have external capital because their own capital is insufficient to ensure consumption growth (Petrick, 2005; Phan, 2012). Households use cash for expenditure and consumption. Because of sporadic income, poorer households need credit to maintain basic levels of consumption, particularly while maintaining machinery and facing increasing levels of depreciation. Depreciation takes the form of input credit and maintenance is shown as a fixed cost to keep equipment functional. These obligations can be seen in advanced credit that households must repay. If the households repay all the credit, smooth consumption and consumption growth can still be attained (Petrick, 2005; Phan, 2012).

This study uses the demand for credit to explain credit participation, which occurs when an individual or a household maximizes his or her expected utility by taking a loan from credit providers. The decision to take a loan is a rational choice based on the demand for credit. Credit plays an important role in supporting rural households. Access to credit is a key requirement for the growth of the economy and the raising of the living standards of rural communities (Petrick, 2005).

2.2 Participating in Microfinance

Microfinance programmes play a crucial role in supporting rural households' access to microcredit (Petrick, 2005; Phan, 2012). The availability of microfinance enables rural households to invest in new technology, improve their production and productivity and ultimately increase their income and consumption. Therefore, it is important to understand the factors that affect households' participation in microfinance programmes. Understanding these factors can help improve credit access and the implementation of credit policies for rural households. This study reviews both credit rationing theory and the demand for credit to use these theories as guidelines for credit participation.

Credit participation begins with the demand for credit; it assumes that an individual (or household) wants to maximize his or her loan utility. Loans have an opportunity cost or the cost associated with the interest rate. Therefore, an individual or household's decision to borrow money can be seen as a rational choice based on the theory of demand for credit. However, demand for credit alone cannot explain credit participation behaviour because credit is rationed under information asymmetry

conditions (Stiglitz & Weiss, 1981). Lenders cannot charge borrowers at the market price or interest rate because they do not have enough information about borrowers' default risks. Moreover, lenders cannot increase interest rates until interest rate equilibrium is reached in the credit market because they need to ration every loan. This means that, if lenders increase the interest rate until it reaches interest rate equilibrium, marginal borrowers may withdraw, leaving only risky borrowers in the market.

Discrete choice theory discusses credit rationing alongside credit demand theory. The discrete choice theory explains the relationship between utility and an individual's discrete choices, or how an individual maximizes his or her utilities through choices (McFadden, 1973). This theory has been used in many fields, including consumer choice, housing and transport choice, and nonmarket goods (Phan, 2012). The choice theory models household behaviour in the credit market. This model assumes that borrowers take out loans to maximize their utilities. A borrower's demand for credit is affected by decision processes and socioeconomic choices. A binary and polychotomous choice model can be used to describe a borrowers' behaviour and the social economic factors that affect households' participation in the credit market.

In the literature, there are three common estimation methods used to investigate the determinants that affect household participation in microfinance: the probit model, the logit model and the multinomial logit model (Fongthong & Suriya, 2014; Menkhoff & Rungruxsirivorn, 2011; Mpuga, 2008). The probit and logit models are used when households choose between two alternative credit options. The multinomial logit model is used when households have over two options of available credit.

Several studies have used the probit and logit models to investigate factors affecting household participation in microfinance programmes, when a household makes a decision between two forms of available credit (e.g., Coleman, 2006; Fongthong & Suriya, 2014; Li, Gan & Hu, 2011a; Nguyen, 2007). Nguyen (2007) examines the determinants of credit participation of Vietnamese households using the probit model and data from the Vietnamese Living Standard Survey (VLSS) conducted in 1992/93 and 1997/98. Nguyen (2007) shows that age, farm work, household size, and landholding are significant determinants affecting household participation in microfinance schemes.

Li et al. (2011a) use the logit model to investigate borrower characteristics that affect access to rural credit. The authors find that household demographics and socioeconomic characteristics (income, the dependency ratio, household location, access to other credit sources and attitude towards debt), affect rural households' access to microcredit. Other factors include interest rates and loan processing times.

Phan (2012) examines factors that influence rural households' access to microcredit in Vietnam. The author uses the credit accessibility model and data from the 2010 Mekong River Delta (MRD) survey, the 2006 Vietnamese Household Living Standard Surveys (VHLSS) and 2008 panel data. He shows that careers, problems with group lending, poor education level, work skills, and village road access all affect access to microfinance schemes.

Kasali, Ahmad and Ean (2016) examined determinants that affect poor households' access to microfinance programmes in Nigeria and analyse data using the logit model. The data are based on 1,134 microfinance loan borrowers and non-borrowers in South-West Nigeria. The authors find that age, household size, business worth, skill or experience, education level, assets, health status, living standards and income all affect access to microfinance programmes in Nigeria. Significantly, they find that the poor in Nigeria cannot access microfinance programmes because of strict terms and conditions.

Santoso (2016) identifies the determinants that influence rural Indonesian households' access to microcredit programmes. The author uses primary data collected from 605 rural households in the Bantul District, Yogyakarta Province, Indonesia. Binary logistic regression is used to investigate the factors that affect household access to microcredit programmes. The study finds that age, household income, loan duration and interest rate affect rural Indonesian households' access to microcredit programmes.

Ashraf and Ibrahim (2014) pinpoint participation barriers for rural poor in Bangladesh using eight explanatory factors and six demographics in three models. The first model compares non-participants who join microfinance programmes, and another group, which includes participants and non-participants (those who do not join microfinance schemes). The second model compares participants and non-participants. The final model compares non-participants (those who would like to join microfinance programmes), with another group (which includes participants and non-participants, those who do not want to join microfinance schemes). Model 1 shows that barriers to microfinance participation include a lack of education, assets, and a female-headed household. Gender, age, income, land, religion, and a lack of knowledge affect microfinance participation in model 2. Model 3 indicates that barriers to participation in microfinance schemes in Bangladesh are gender, education, land, insufficient resources, and a lack of knowledge. The authors suggest that if microfinance programmes in Bangladesh want to reduce barriers, they should improve high-cost loans by changing institutional features to decrease the cost, membership criteria and repayment systems.

Sebatta, Wamulume, and Mwansakilwa (2014) investigated the determinants that affect smallholder farmers' access to rural finance. Primary data are from five provinces in Zambia. The authors use the

probit model and find that the household head's education level, household size and the number of daily meals served significantly influence household participation in rural finance. Personal savings, having a phone and the loan maturity date affect participation levels in agricultural finance.

Saqib et al. (2016) explored the factors that influence Pakistani farmers' access to agricultural credit using a probit regression model and primary data from 168 farmers. The results show that age, education, farming experience, family size, and income affect farmers' ability to access agricultural credit. The authors recommend that the government should develop agricultural credit policies to help small farmers in the event of natural disasters.

Tang, Guan and Jin (2010) identify socioeconomic factors that influence farmers' decisions to change from formal credit systems to an informal credit one in China. They use primary data from 471 households in 28 Chinese villages. The authors use the probit model to investigate factors that affect farmers' access to loans and the multinomial probit model to identify the determinants affecting farmers' choice of loan source. The results of the probit model show that household size, agricultural land and household head's education levels significantly influence households' ability to borrow and likelihood of borrowing. The multinomial probit model shows that household size, education and land area increase households' probability of accessing loans from formal credit markets.

Using the logit model, Coleman (2006) investigated the characteristics of village bank members. The author uses data from 444 households in 14 villages in northeast Thailand. Coleman finds that the value of land owned by women, creditworthiness score and female household head significantly affect participation in the programme; wealthier villagers are more likely than poorer villagers to participate in the programme.

Fongthong and Suriya (2014) evaluated the VF used to reach the poor in Thailand. The authors use the logit model to investigate borrower determinants. They used data from Thailand's 2009 Socioeconomic Survey. They find that the VF borrowers are near-poor and moderate-income households. The determinants that influence the borrowers are female committees and households with more members.

Dufhues, Buchenrieder and Munkung (2013) investigated the determinants that affect households' access to formal credit in north Thailand. The authors focus on social capital variables that impact formal credit access. They used primary data collected from the Chiang Mai Province and logit regression for empirical analysis. The authors find that household head's age, social capital, the dependency ratio, past credit, location of the house, being a member of the ethnic majority (Thai) and the possession of an identification card affect formal credit access.

Several studies have used the multinomial logit model to investigate the factors affecting microfinance participation (e.g., Balogun & Yusuf, 2011; Durojaiye, Yusuf & Balogun, 2014; Eularie & Vishwanatha, 2016; Menkhoff & Rungruxsirivorn, 2011; Mpuga, 2008). Mpuga (2008) investigated credit access and demand in rural Uganda. The author uses secondary data from Ugandan household surveys conducted in 1992/93 and 1999/2000 and uses the probit, tobit and multinomial logit models to analyse the data. The probit model is used to predict factors associated with an individual's or household's decision to apply for credit and the tobit model is used to investigate the factors that affect loan size (the amount that borrowers are able to take). The multinomial logit model is used to investigate the individual or household characteristics that affect access to different sources of credit. The author finds that age, education level, gender, occupation, the value of household assets and dwelling characteristics strongly influence access to credit, whereas age, education level, location, dwelling characteristics, occupation, and household wealth affect an individual's or household's access to different sources of credit. The author also finds that age, education level, gender, occupation, marital status, the value of household assets, location and dwelling characteristics are related to loan size.

Durojaiye et al. (2014) examined the factors that influence the demand for microcredit in southwest Nigeria. They use a multinomial logit model to analyse their data. They find that social capital variables (trust index, decision-making index, labour contribution, meeting attendance index and heterogeneity index) and credit variables (interest rate, credit distance, and payback period) explain the demand for credit. Their study suggests that social networks need to be developed so that borrowers are more aware of lending schemes. This knowledge can improve borrowers' access to credit. As a result, borrowers can improve their income.

Using descriptive statistics and a multinomial model, Balogun and Yusuf (2011) determined the factors that affect demand for microcredit among rural households in Ekiti and Osun, Nigeria. They use primary data for household demographic characteristics, social capital and microcredit variables. The authors' multinomial logit results show that household social capital variables (membership density index, meeting attendance index, cash contribution index and heterogeneity index), the dependency ratio and credit variables (credit distance and interest rate) significantly explain a household's demand for credit.

Eularie and Vishwanatha (2016) used a multinomial logit model to investigate the factors that influence small farmers access to microfinance programmes. They use primary data from 300 small farm households in the Huye District, southern Rwanda. The authors find that the area of land, distance, annual interest rate, age, off-farm income, and household size significantly influence household access to microcredit programmes.

Using data from the National Finance Access (FinAccess) survey (2009), Wachira and Kihui (2012) evaluated the impact of financial literacy on access to financial services in Kenya. They used the multinomial logit model to investigate the factors that affect individuals' access to financial services. Income, distance from a bank, education level, gender, age, household size, and marital status significantly influence access to financial services. Notably, access to financial services is not related to financial literacy. The authors also show that financial literacy is low in Kenya and recommend that the government increase the funding for community financial literacy programmes.

Chen and Jin (2017) explored the determinants affecting Chinese households' decisions to borrow from both the formal and informal sectors. The authors used data from the 2011 China Household Financial Studies and analyse it using the multinomial logit model. The authors find that marital status, age, employment, education, Communist party membership, household location, annual income, and net worth significantly influence a household's access to formal credit. Similarly, marital status, age, employment, education, household location, annual income, and net worth significantly affect a household's access to informal credit. The factors affecting households using both sources of credit are marital status, age, employment, education, household location, and net worth. The authors recommend that the Chinese government introduce financial literacy training.

Using a multinomial logit model and secondary data from the 1998 Vietnam Living Standard Survey (VLSS), Pham and Lensink (2007) investigated the factors affecting Vietnamese households' access to various sources of credit. Their results show that income, gender, collateral, guarantors, and borrowing for their business affect households' access to loans from both formal and semi-formal institutions. They find that poor households and female household heads are more likely to borrow from informal credit sources.

Menkhoff and Rungruxsirivorn (2011) used the multinomial logit model to compare borrowers' characteristics between VFs and six other financial institutions in three provinces in northeast Thailand. They find that loan source determinants are age, a female household head, the number of children, occupation, income, land holding, assets, the default loan ratio, and loan characteristics.

Using primary data from 2007 and 2008 from three provinces in northeast Thailand, Ubon Ratchathani, Buriram and Nakhon Phanom, Kislat and Menkhoff (2012) evaluated the role of VFs. The authors divide borrowers into four groups: those who took a loan in the first year but not in the second year; those who took a loan in the second year; those who took a loan in both years; and those who have never taken a loan. They used the multinomial logit model to investigate VF borrower characteristics. They find household size, income and occupation influence households' access to VFs.

As the previous studies reveal, three main methods have been used to investigate factors that affect rural households' access to MFIs. These methods are: the probit, logit, and multinomial logit models. As seen in the preceding paragraphs, the factors that affect household participation in microfinance programmes include household head characteristics and demographics (household size, the dependency ratio, occupation, income, and assets). Significantly, most studies that investigated factors that affect households' participation in the VF in Thailand focus on northeast Thailand. Coleman (2006) investigated the characteristics of village bank members in northeast Thailand using the logit model; Kislat and Menkhoff (2012) evaluated the role of VFs from three provinces in northeast Thailand. Coleman states that northeast Thailand is the country's poorest region. However, no studies have investigated the determinants affecting household participation in both VFs and SGPs in Thailand. Studies have shown that, in Thailand, most low income and poor people can access financial services from community-based MFIs, such as VFs, cooperatives, and SGPs (Microfinance Services Ltd., 2013; Tambunlertchai, 2015). This study will identify the determinants that affect borrowers' decisions to participate in VFs and SGPs in Thailand.

2.3 Microfinance Impact Evaluation

Microfinance programmes have had an impact on the poor, both in increasing their income and in increasing consumption. Microfinance programmes can create a virtuous circle for the poor (Islam, 2007). The circle starts with the poor taking out a loan for investment. As a result, they earn more income. They are then able to take out a larger loan to increase investment and earn more income. The continuous growth in income then increases household consumption. In other words, microfinance programmes can improve borrowers' welfare. Moreover, improving income by microfinance loans encourages the poor to increase investment in working capital (such as seeds, raw materials and fertilizers) and assets (e.g., machinery and cash savings). Capital and asset accumulation improve borrowers' income-generating capabilities (Armendariz de Aghion & Morduch, 2005; Islam, 2007; Phan, 2012).

Microfinance programmes also contribute to borrowers' productivity, which can improve their overall economic condition (Islam, 2007). Microfinance programmes provide small loans that allow the poor to invest in high-yielding varieties and advanced technology, which ultimately improves productivity and promotes higher production levels (Li, 2010). These improvements are crucial factors in reducing poverty. Microfinance programmes also create employment opportunities for the poor; they can use loans to establish their own businesses. As self-employment expands, more labour is needed and employment rates improve. Microfinance programmes have been universally applauded for reducing poverty and improving poor households' well-being through providing a

more stable income base, increased consumption and employment opportunities (Armendariz de Aghion & Morduch, 2005; Islam, 2007; Phan, 2012).

However, accurately measuring the impact of microfinance programmes is difficult because of a lack of information (Caliendo, 2006). This problem persists in non-experimental or observational studies, which tend to have gaps in their data through a lack of information (Caliendo, 2006). Researchers can observe differences in outcomes between those who participate and those who do not participate in microfinance schemes (Caliendo, 2006; Phan, 2012). However, impact evaluation requires comparisons between two potential outcomes for the same individual; one with the treatment and the other without. In short, researchers cannot observe both situations for a particular individual simultaneously (Kono & Takahashi, 2010). The following section reviews the literature on MFI impact evaluations.

2.3.1 Impact Evaluation Frameworks

Hulme (2000) constructed a model of impact assessment (IA) and a framework of impact assessment (IA) (see Figure 2.3). The aim of impact assessment is to compare the differences in outcomes between agents who experience microfinance programmes against outcomes with the same agents without microfinance programmes. There are three steps to IA: define the agents (assessment unit); define the outcomes (assessment indicators); and assessment.

To illustrate how impact evaluation works, we must assume that there is a microfinance scheme assigned to a target group of households and that there are two variables, d , and Y . Here d is defined as the binary choice variable of microfinance participation. We suppose that $d = 1$ if a household or individual participates in a microfinance scheme, and $d = 0$ otherwise. Y is the outcome value of microfinance participation. The outcome depends on microfinance participation; that is, $Y = Y_1$ if $d = 1$, and $Y = Y_0$ if $d = 0$. The impact of microfinance participation on the outcome of the i^{th} household or individual, which is represented by Δ_i , can be measured as follows (Hulme, 2000; Phan, 2012):

$$\Delta_i = Y_{i1} - Y_{i0} \quad (2.22)$$

The impact of microfinance participation in equation (2.22) is equal to the difference in the outcome between the microfinance programme state and non- microfinance programme state. The outcome cannot be observed because the same household or individual cannot participate or not participate at the same time. This problem is a counterfactual situation (Heckman, Ichimura, & Todd, 1997). The microfinance impact cannot be estimated because of it. Kono and Takahashi (2010) and Stuart (2010) note that the Average Treatment Effect (ATE) and the Average Treatment Effect on the Treated (ATT) are commonly used to evaluate the microfinance impact because these methods can directly measure the microfinance impact on the target group.

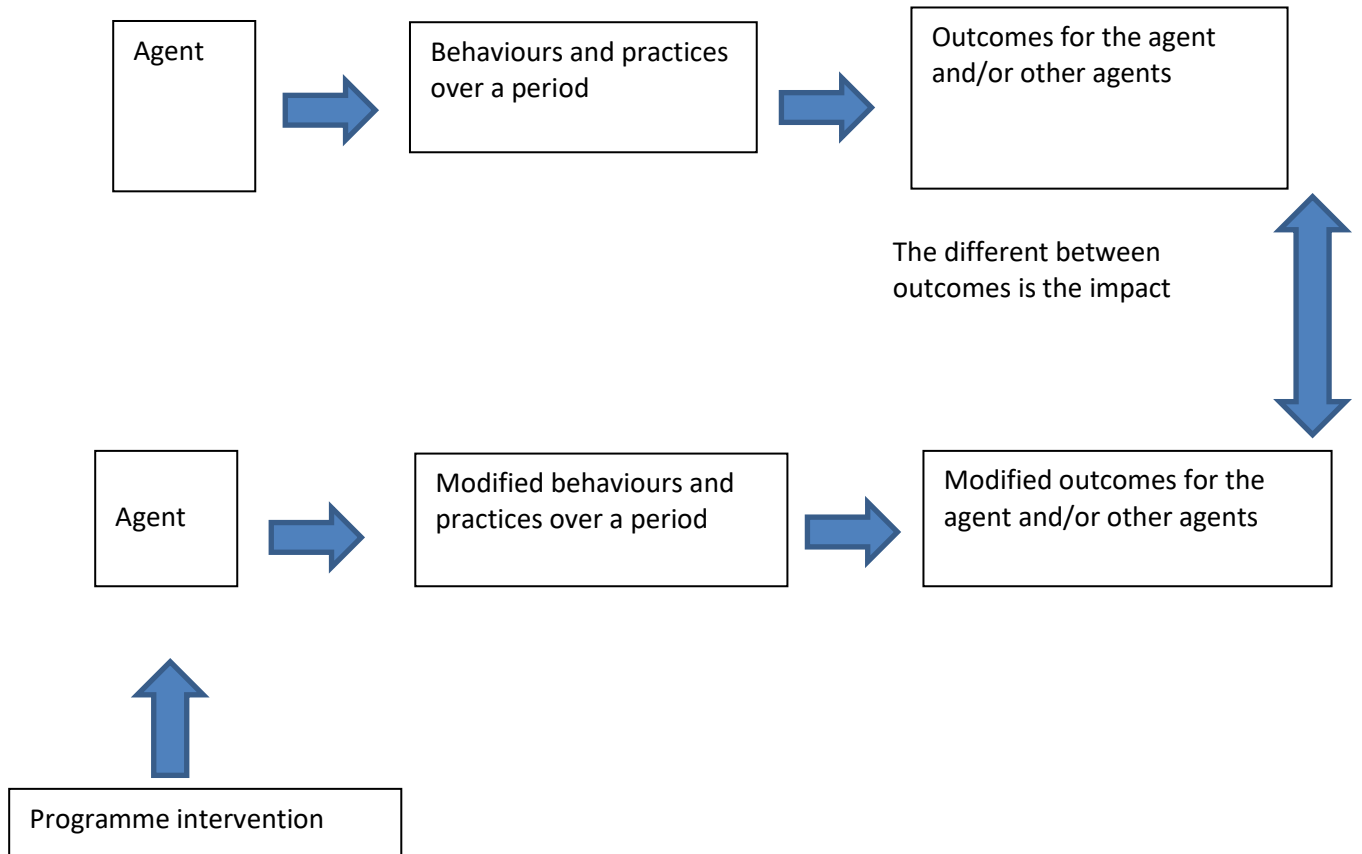


Figure 2.3 A Model of Impact Evaluation

Source: Adapted from Hulme (2000)

ATE measures the impact of programme participation on individuals or households randomly selected and assigned to the programme, whereas ATT measures the impact of programme participation on individuals or households who actually participated in the programme (Kono & Takahashi, 2010). ATE can be shown as:

$$ATE = E(Y_1 - Y_0) \quad (2.23)$$

$$ATE = E(Y_1|d=1) - E(Y_0|d=0)$$

In equation (2.23), $E(\cdot)$ is an expectation operator. ATE shows the expected effect of the treatment on the individuals or households randomly drawn from the population.

In equation (2.24), d is the binary choice variable of microfinance participation. We suppose that $d=1$ if a household or individual participates in the microfinance scheme and $d=0$ otherwise. ATT can be expressed as:

$$ATT = E(Y_1|d=1) - E(Y_0|d=1) \quad (2.24)$$

Assuming that the study can observe both Y_1 and Y_0 for any individual or household, the average difference between ATE and ATT should be attributable to participation in the microfinance

programme. If $E(Y_1 - Y_0)$ and $E(Y_1/d=1) - E(Y_0/d=1)$ are positive, microfinance has a positive impact on the outcome of interest and vice versa.

ATE and ATT differ from each other because the outcome depends on programme participation; therefore, $E(Y_1) \neq E(Y_1/d=1)$ and $E(Y_0) \neq E(Y_0/d=1)$. This study evaluates the impact of microfinance participation on borrowers' economic and social welfare using the ATT method. However, the ATT method cannot be estimated directly because some components in equation (2.24) cannot be directly observed. In the next sub-section, I discuss the methods used to solve the counterfactual problem.

2.3.2 Impact Evaluation Methods

There are statistical methods that can be used to construct the counterfactual. These methods include: (1) the Matching method; (2) the Instrument Variables method; (3) the Regression Discontinuity design; and (4) the Difference-in-Difference approach. Each method has its strengths and weaknesses.

The primary goal of the matching method is to find a control group that is the same or like the treatment group, except for the treatment status (Kono & Takahashi, 2010). The similarity of the two groups is identified from their observable characteristics. A key assumption of this method is that the observable characteristics and participation in a microfinance programme are independent of the outcome of interest (Kono & Takahashi, 2010). The matching techniques include propensity score matching (PSM), caliber and radius matching, nearest neighbour matching and kernel matching (Stuart, 2010). The benefit of these techniques is that they can be used to obtain the impact coefficient to solve the selection bias from the observable characteristics. However, matching does not solve the selection bias resulting from unobservable characteristics such as entrepreneurial drive, and the internal risk status of rural farmers (Marr, 2012). Several studies have used the matching model to evaluate microfinance impact on households (e.g., Cintina & Love, 2014; Setboonsarng & Parpiev, 2008; Swain & Floro, 2012). Setboonsarng and Parpiev (2008) studied the impact of the Khushhali Bank (KB) in Pakistan. The authors use 2005 data from Montgomery (2005) to evaluate the impact of KB on economic and social issues. The authors use the PSM method to address selection bias. They show that KB contributes positively and significantly to income generation activities but it only marginally affects education, health, and female empowerment.

Swain and Floro (2012) investigated the Self-Help Group (SHG) in India that was established to reduce poverty and household vulnerability. The authors use cross-sectional SHG rural household survey data from 2003. They use the PSM method to investigate whether SHG leads to a reduction in poverty and household vulnerability. They show that SHG members' vulnerability is not significantly

higher than non-SHG members even though SHG members have a high poverty incidence. However, SHG members' vulnerability reduces significantly after they have been members for a year.

Cintina and Love (2014) compared the microfinance impact on MFI borrowers' expenditure. The authors use data from Banerjee et al. (2014) and the PSM method to evaluate the impact of microfinance loans on expenditure and find that microfinance borrowers exhibit higher expenditure in several categories, notably durables, household repairs, health, festivals, and temptation goods.

The second approach is the instrumental variables method (IV). The main point of this method is to control the selection bias from unobservable characteristics by finding a variable that determines microfinance participation but does not influence the outcome (Kono & Dias, 2000). Three conditions make the IV method valid (Kono & Takahashi, 2010). First, an instrumental variable influences the decision to participate in microfinance schemes. Secondly, the instrumental variable does not affect the outcome. Finally, the instrumental variable is uncorrelated with the error term and entirely determined by the independent variables in the model. Unlike the matching models, this method can solve the bias from unobserved factors that affect participants' decisions. Previous studies that use the IV method to evaluate microfinance impact include Cuong (2008), Khandker and Faruquee (2003) and Pitt and Khandker (1998). Cuong (2008) evaluated the impact of microcredit programmes in Vietnam using two methods to measure the impact: instrumental variables regression and fixed-effect with instrumental variables regression using panel data. Cuong used Vietnam Household Living Standards Survey (VHLSS) data from 2002 and 2004. The author finds that microcredit programmes are not very pro-poor, particularly in terms of targeting. However, the programme did reduce participants' poverty rate.

Khandker and Faruquee (2003) studied the impact of farm credit on household welfare in Pakistan using IV and household survey data from rural Pakistan collected by the Rural Financial Market Studies (RFMS). The authors find that loans contribute to better household welfare and consumption and production were higher for small landholders than for large holders.

Burgess and Pande (2002) evaluated the impact of rural banks on poverty reduction in India using IV. They use Central Bank data collected between 1961 and 2000. They find that rural bank branch expansion significantly affects economic growth and total per capita output. Non-agricultural outputs, in particular small-scale manufacturing and services, are most impacted by rural bank branch expansion.

Regression discontinuity design (RDD) works best for individuals who are at the cut-off point of programme eligibility (Kono & Takahashi, 2010). For example, suppose the microfinance scheme identifies the target group using the number of landholders. If individuals have less than 1 hectare of

land, they are eligible to participate in the programme. MFIs use this criterion to select borrowers. The assumption in this method is that both the observable and unobservable characteristics of households are uncorrelated with eligibility (Kono & Takahashi, 2010). Based on this assumption, this method compares the outcomes of individuals who are just below and above the cut-off point for eligibility. This means that RDD can solve the bias from participating decisions that affect the decision rules. The main drawback of RDD is that the selection criteria are not always clear (White & Sabarwal, 2014). The microfinance programme cannot distinguish precisely between eligibility criteria, therefore, behavioural responses to microfinance programme intervention may be confused (Khandker, Koolwal, & Samad, 2010). Several studies have used RDD to evaluate microfinance impact (e.g., Aktaruzzaman & Farooq, 2016; Pitt & Khandker, 1998). Pitt and Khandker (1998) use the regression discontinuity design to estimate the impact of group-based credit programmes on poor households in Bangladesh by identifying the target households that own less than half an acre of land. The results show that microcredit increases household consumption and improves children's schooling. The authors also find that the poor can access microcredit schemes and that these significantly reduce poverty levels.

Aktaruzzaman and Farooq (2016) examined the impact of participation in microcredit programmes on consumption. They use RDD to identify the credit impact based on data collected from 69 villages in Bangladesh. The authors find that access to the programmes decreases per capita expenditure on durable goods while increasing the expenditure per school-going child and on non-durable goods, health care, recreation and gifts.

A popular evaluation method is the Difference-in-Difference method (DID). The basic idea of this method is a combination of before after comparisons and with-without comparisons (Kono & Takahashi, 2010). This method can compare changes over time in observed outcomes of participants with those of non-participants. This method requires data from before and after microfinance programme implementation. The main assumption of this method is time-invariant assumptions of unobservable variables. The assumption means that unobservable variables that affect programme selection do not change over time (White & Sabarwal, 2014). The main advantage of this method is that it can solve selection bias related to the programme based on unobserved factors. However, a major disadvantage of this method is that it requires panel data that must be collected before and after the programme. This is a violation of the time-invariant assumption (White & Sabarwal, 2014). Some studies have used DID to evaluate microfinance impact (e.g., Chandoevrit & Ashakul, 2008; Coleman, 1999).

Using data from 445 households in 14 villages in northeast Thailand, Coleman (1999) examined the impact of village banks on assets and income. DID was used to compare participating and non-

participating households and between villages where the programme has been introduced and those where it has not. The author finds no evidence of programme impact. In short, the village bank has no visible impact on assets and income.

Chandoevrit and Ashakul (2008) investigated the impact of the VF in Thailand on household income, expenditure and poverty rate. With data from the 2002 and 2004 Socioeconomic Surveys, the authors use both the PSM and DID to measure the impact on income, expenditure and poverty. The results show that the VF does not alleviate household poverty. The VF increases farm income only in the central region and non-consumption expenditure (expenditure on taxes, gifts, insurance premiums, donations, gambling and interest payments) in the northern and southern regions.

To estimate the different impact of microfinance, these methods rely on specific assumptions. This can lead to questions about the validity of the results. The next section examines recent literature on the impact evaluation of microfinance programmes.

2.3.3 Impact Evaluation Studies

Understanding the literature on impact evaluation is crucial for ensuring scholars design better methods to evaluate the impact of microfinance schemes. Pitt and Khandker's (1998) study of rural areas in Bangladesh tried to address the sample selection bias by constructing a quasi-experimental design survey, which mitigates bias arising from unobserved individual and village-level heterogeneity. Pitt and Khandker (1998) used a regression discontinuity design to estimate the impact, by identifying target households that owned less than half an acre of land. The results show that microcredit increases household consumption and improves children's schooling. The authors also find that the poor have access to microcredit schemes and that these programmes significantly reduce poverty levels.

Morduch (1998) argues that Pitt and Khandker's (1998) study violates the eligibility criterion of less than half an acre of landholding. The land market in Bangladesh is rather active. This means that clients in the programme can sell and purchase land easily. In short, Morduch suggests that the impact estimation is erroneous. Morduch overcomes this problem by adjusting the sample to maintain comparability. He uses an instrument approach estimation.

In a similar quasi-experimental design, Coleman (1999) addressed the selection bias problem using 445 households' data (from 14 villages in northeast Thailand). The villages are divided into two groups. The first group has eight villages. These villages have had banks since 1995. The second group is six villages that have village banks (the banks have been established but are not currently operating). In the second group, households have waited over a year for the bank to grant them a first loan. Coleman uses households in this group as a control group and applies the DID method to

compare production, physical assets, income, savings, and expenditure. Coleman finds that membership of a village bank has no impact on household assets and income. Coleman's findings thus differ from those of Pitt and Khandker (1998) in that the impact is not significantly different from the control group.

However, Coleman (1999) assumes that old and new borrowers' characteristics do not change over time. This assumption may be unrealistic (Armendariz de Aghion & Morduch, 2005). If the borrowers' timing of entry is because of motivation, ability and entrepreneurship, Coleman's (1999) comparison may do little to solve the selection bias and could exacerbate it (Armendariz de Aghion & Morduch, 2005).

The biases in Coleman's (1999) study are because microfinance programme participants drop out; this can be a problem in cross-sectional data when comparing the impact between old borrowers and new borrowers (Alexander-Tedeschi & Karlan, 2002; Karlan, 2001). In short, borrowers might graduate from microfinance programmes because they do well in their business and no longer need assistance. In this case, the impact of microfinance is underestimated. Conversely, some borrowers may have had trouble in their business and left the programme. In this case, the impact is overestimated.

To solve the selection bias and drop-out problem, Marr (2012) reviewed theories and econometric techniques. Marr recommends propensity score matching. This method compares borrowers and non-borrowers based on the probability of participation in microfinance programme, conditional on a set of observed characteristics (Cintina & Love, 2014). Although this method can account for the bias from observed characteristics, the technique cannot solve bias from unobserved characteristics (Marr, 2012).

Several studies use the PSM method to study microfinance's impact. Setboonsarng and Parpiev (2008) studied the microfinance impact of the Khushhali Bank in Pakistan. The authors use data from Montgomery (2005) to evaluate the impact of the KB on economic and social issues. The authors use the PSM method to address selection bias. Their results show that the KB contributes significantly, positively to income generation, but only marginally affects education, health and female empowerment. They use cross-sectional data that are prone to incorrect inference because the microfinance impact is spread over time. Therefore, the time element should be included to reflect the true microfinance impact.

Swain and Floro (2012) investigated the Self Help Group in India. It aims to reduce poverty and household vulnerability. The authors use cross-sectional SHG rural household survey data from 2003. They employ the PSM method to investigate whether the SHG leads to a reduction in poverty and

household vulnerability. Their results show that SHG members' vulnerability is not significantly higher than non-SHG members. However, SHG members' vulnerability reduces significantly after they have been SHG members for over one year. Swain and Floro (2012) claim that their results are robust because they use sensitivity analysis to test the results' robustness.

Cintina and Love (2014) compared the microfinance impact on MFI borrowers' expenditure between treated and untreated groups. In the first group, the authors compare expenditure for MFI borrowers and non-borrowers. In the second group, they compare expenditure for MFI borrowers and informal borrowers. The authors use data from Banerjee et al. (2014) and the PSM method to evaluate the impact of microfinance participation on expenditure. Cintina and Love (2014) find that MFI borrowers exhibit higher expenditure in several categories: durables, household repairs, health, festivals and temptation goods. The authors tested the robustness of their results by presenting four different matching methods. The standard errors for all four different matching methods are calculated using bootstrap simulations with 100 repetitions. This means the propensity scores are estimated. The robustness tests reveal that the four matching methods produce similar results.

Some researchers use more than one approach to solve observed and unobserved biases. Phan (2012) investigated the impact of the Vietnam Bank for Social Policy (VBSP) on household consumption and income using PSM and the fixed effect model with instrumental variables. Phan uses 2010 Mekong River Delta (MRD) data and the Vietnam Household Living Standard Surveys (VHLSS). PSM and instrument variables-fixed effect model confirm that the formal credit programme has a positive impact. The PSM method shows a positive, significant impact on household consumption. Phan's study, however, suffers from inconsistent impact estimators from the IV-FE models because instruments encountering endogeneity likely face weak instrument identification.

Chandoevwit and Ashakul (2008) evaluated the impact of VF on household income, expenditure and poverty rates in Thailand using PSM and DID with data from the 2002 and 2004 Socioeconomic Surveys. Their results show that the VF has not alleviated the country's poverty. The VF increases farm income in only the central region and non-consumption expenditure (including expenditure on taxes, gifts, insurance premiums, donations, gambling and interest payments) in the northern and southern regions.

Boonperm et al. (2013) evaluated the impact of the VF on income and spending in Thailand using both PSM and the fixed effect model. They use data from the 2002 and 2004 Socioeconomic Surveys. Boonperm et al. (2013) find that the VF increases the poor's income by 1.4% and spending by 3.5%. Their results also show that the VF's effect on expenditure is strongest in the lower quantiles and flows disproportionately to low-income households. These results demonstrate that the VF is pro-poor.

No studies have simultaneously evaluated the impact of both VF and SGPs on economic and social welfare in Thailand. This study evaluates the impact of both the VF and SGPs on participants' economic and social welfare in Thailand. As a result of the literature review, I use both PSM and the fixed effect method because these methods can solve observed and unobserved biases.

The following section reviews the literature on the economic and social welfare impact of microfinance. Though economic welfare impact covers income, savings, expenditure, assets, consumption and investment, the social welfare impact is education and healthcare. The literature review shows that there are problems with selection bias. Many studies use more than one method to overcome selection bias. For example, Phan (2012) studied the impact of the Vietnam Bank for Social Policy (VBSP) on household consumption and household income using both PSM and the fixed effect model with instrumental variables. Similarly, Chandoevmit and Ashakul (2008) investigated the impact of the VF in Thailand on household income, expenditure and poverty rate. They used PSM and the DID method.

2.4 Assessment of MFIs' Performance

Although microfinance programmes play an important role in improving both the economic and social welfare of the borrowers, MFIs cannot help borrowers if their own performance is poor. This section reviews the literature on MFI performance assessment and, in particular, poor MFI performance.

MFI performance assessment involves evaluating progress and determining whether an MFI has achieved its goals. The most important goal of all MFIs is to improve the living standard of the poor and to eradicate poverty. There are three stakeholders to consider when discussing MFI performance: borrowers, donors and microfinance staff (Schreiner, 1996).

Borrowers measure MFI performance by their access to the scheme. For example, when borrowers obtain microfinance loans, they can improve their business, provide healthy food for their family and pay for their children's education. In short, microfinance loans can improve borrowers' general wellbeing (Schreiner, 1996). Islam (2007) reveals that the poor borrow money to invest. As a result, they can earn more income. As their investments pay off, they can increase the size of their loans and earn more money; continued income growth can increase household consumption.

Donors measure MFI performance using market leverage. Market leverage shows how MFIs can achieve particular goals with the donations given (Schreiner, 2003). For example, outreach to the poor should increase as donations increase. Equally, as donations increase, MFIs should become more stable and efficient in providing the services. Navajas et al. (2000) point out that though MFIs provide credit to poor households, most of these poor are the richest amongst the poor. Quayes

(2015) argues that funding agencies prefer outreach effort. Outreach effort demonstrates that an MFI is reaching the poor and is ensuring the efficient use of funds.

Borrowers and donors measure MFI performance using social performance indicators (Copestake, 2007; Islam, 2007; Schreiner, 1996). According to Copestake (2007), there are three sets of indicators used to evaluate an MFI's social performance (the breadth of outreach, depth of outreach and quality or impact of outreach). Copestake defines the breadth of outreach as the number of people using microfinance products in a given period of time. Depth of outreach shows the initial social status of MFI clients. Quality or impact of outreach shows the net benefit to each client. This includes indirect benefits to other households and non-household members during the given time period (Copestake, 2007).

Mosley and Rock (2004) state that the poor benefit via three indirect routes. Firstly, if microfinance programmes do provide loans to the poor, these loans can decrease poverty by drawing very poor people into labour market to work as employees. Borrowers from microfinance programmes hire the very poor people in their business. This can improve income of the very poor. Secondly, microfinance often improves human capital through educational expenditure. Borrowers often use the money on health-related expenses and thus, have better health. Spending the loan money on education and health may have intrahousehold and inter-generational effects. Finally, microfinance also often improves a household's risk management because it enhances their social capital. Borrowers can participate in training arranged by MFIs. In addition, borrowers can build up their social networks. Borrowers can share information about the market, prices and technology. They can also cut costs by pooling their resources to transport goods to and from the markets and by sharing storage facilities (Mosley & Rock, 2004). These actions may reduce the very poor's vulnerability to risk and stabilise a village's income (Mosley & Rock, 2004). Woller and Parsons (2002) contend that indirect impacts of microfinance programmes can be evaluated using employment levels. According to the authors, their results reveal that the economic benefits of microfinance programmes extend beyond programme beneficiaries.

The final group, microfinance staff, evaluate MFI performance using financial self-sufficiency (FSS) (Schreiner, 2003). FSS is important for staff because they will have a job when donors leave (Mokhtar, 2011). Quayes (2015) states that most MFIs operate as non-profit organizations because they provide loans to the poor to facilitate poverty alleviation. Some microfinance programmes operate using profit maximization principles (with no outreach goals). This reflects a paradigm shift in microfinance programmes, from subsidized credit to financial sustainability. However, MFIs can have both outreach and sustainability goals, without these being at odds with one another (Quayes, 2015).

Quayes (2105) suggests that MFIs should diversify their asset-liability portfolios and access funds from deposits.

Evaluating MFI performance can be done using three criteria, what are referred to as the triangle of microfinance (Zeller & Meyer, 2002). These criteria are outreach, financial sustainability and welfare impact. Outreach refers to the total number of poor, including the total number of women, who are served by microfinance programmes (Mokhtar, 2011). This criterion means that microfinance programmes can reach the poorest with a variety of financial services. Financial sustainability is measured using 11 financial performance indicators: portfolio at risk, the provision expense ratio, the risk coverage ratio, the write-off ratio, the operational expense ratio, cost per client, personnel productivity, credit officer productivity, the funding expense ratio, the cost of funds ratio, and loan loss reserves (Mokhtar, 2011). The welfare impact is measured by the benefits borrowers gain from the programme. This measurement is essential in determining the success of a microfinance programme. Welfare information is used by donors and governments to justify their investment in the programme.

Mokhtar (2011) points out that microfinance welfare impact measurement is essential in determining the success of microfinance programmes. The author explains that donors and governments can use the welfare impact measurement to justify their investment in terms of improving borrowers' socioeconomic position. Islam (2007) states that microfinance loans increase borrowers' production levels and reduce their poverty levels. This means that the success of a particular microfinance programme is shown by positive changes in borrowers' production levels, household welfare and personal lives.

Many researchers measure MFI performance using a welfare only perspective impact (e.g., Coleman, 1999; Pitt & Khandker, 1998; Setboonsarng & Parpiev, 2008; Swain & Floro, 2012). Some researchers focus solely on outreach (e.g., Navajas et al., 2000). Others examine both outreach and financial performance (e.g., Bhuiyan et al., 2011; Cull, Demirguc-Kunt, & Morduch, 2007; Kereta, 2007; Quayes, 2015). Very few studies simultaneously measure performance from an impact, outreach, and financial perspective. This study evaluates the microfinance impact on economic and social welfare as outlined in objective two. To fulfil the third objective, the study focuses on MFI performance; it examines Thai VFs' and SGPs' outreach and financial performance.

Agarwal and Sinha (2010) analyses MFI financial performance in India using six parameters of financial performance: financial structure, revenue, expenses, efficiency, productivity, and risk. These parameters are comprehensive and are globally accepted indicators of MFI financial performance (Agarwal & Sinha, 2010). Agarwal and Sinha also use financial performance to capture the holistic picture of MFI performance. Financial performance is defined as whether an MFI is profitable enough

to maintain and expand its services without subsidies (Rosenberg, 2009). This means financial performance contributes to an MFI's financial sustainability (Eur-U-Sa, 2011). Financial performance covers three ratios: return on assets (ROA), return on equity (ROE) and operational self-sufficiency (OSS). MFIs are profitable and sustainable if they exhibit positive ROA and ROE and have an OSS value over 100% (Bassem, 2012). OSS is a ratio that shows whether operating income is enough to cover operating costs including salaries, loan losses and other administrative costs (Arthur et al., 2013). OSS over 100% means that MFIs can run their business without funding or subsidies from external sources (Schäfer & Fukasawa, 2011).

Agarwal and Sinha (2010) uses data from 22 MFIs obtained from the 5-star rated performers of the Mix-market database. Data are analysed using different means tests to compare the performance of the 22 MFIs. The authors find that, in India, most of the best performing firms follow different business models. However, their study is limited because the data are of 5-star rated performers from the Mix-market database. The Mix-market database has information about MFIs' performance for only 22 MFIs in India. If the authors used a broader sample, the results may be different.

Using the same indicators as Agarwal and Sinha (2010), Bhuiyan et al. (2011) compared the financial sustainability and outreach of MFIs in Malaysia and Bangladesh. The data are from the 2008 Annual Report and the Mix-market database. Their results show that MFI performance in Malaysia is better than MFI performance in Bangladesh, in terms of OSS, earnings and expenses, but the performance is lower in terms of outreach and efficiency.

Rahman and Mazlan (2014) compared the financial performance of five MFIs in Bangladesh. The authors use financial structure and financial performance as performance indicators. They use secondary data from the Mix-market database for the period 2005 to 2011. They conclude that the five Bangladeshi MFIs are financially sustainable because they exhibit positive ROE and ROA values.

Financial structure is defined as the specific mix of long-term debt and equity that an MFI uses to finance its operations (Kar, 2012). The funding composition directly affects a business's value (Kar, 2012). The financial committee should decide how much money to lend and the best mixture of debt and equity (Kar, 2012) and must find the least expensive source of funds.

Bayai and Ikide (2016) conclude that MFIs whose objective is to maximize profit can employ debt, equity and savings. In contrast, donations, subsidies, and grants are used by NGOs. Debt is supplied by commercial banks, investors (non-commercial) and multilateral organizations. Developing banks and non-profit organizations play a role as investors by holding equity in an MFI (Bayai & Ikide, 2016). Bayai and Ikide (2016) investigate how MFIs are financed globally. The authors show that 25% to 35%

of MFIs use savings/deposit financing, 35% to 40% of MFIs use debt financing and 30% to 40% of MFIs use equity financing (Bayai & Ikide, 2016).

This section reviewed the literature and concludes that there are three ways to evaluate microfinance institutions' performance. They are: outreach, welfare Impact, and financial self-sufficiency. This study focuses on outreach and financial self-sufficiency and investigates the performance of VFs and SGPs. We compare both VFs' and SGPs' performance in terms of institutional characteristics, outreach, productivity, financial structure and financial performance in a similar manner to Agarwal and Sinha (2010), Bhuiyan et al. (2011) and Rahman and Mazlan (2014). The data are from annual reports like in Bhuiyan et al.'s (2011) study.

2.5 Microfinance Financial Sustainability

Microfinance financial sustainability can be affected by several factors. Kinde (2012) argues that financial sustainability is key to microfinance institutions' sustainability. Financial sustainability means that an MFI can cover all its costs from its income without subsidies (Kinde, 2012). Dunford (2003) defines financial sustainability as an MFI's ability to achieve its objectives without donor support. These definitions emphasize self-operation sustainability (Kinde, 2012).

There are two levels of financial sustainability (Meyer, 2002). The first level relates to MFI achievement and is a lower level. The OSS level means that operating income is sufficient to cover operating costs, such as salaries and wages, supplies, loan losses and other administrative costs. The second standard level is FSS, which means that an MFI can cover both its operating and financing costs and other forms of subsidies, valued at market prices.

Very few studies explore the determinants of MFIs' sustainability. Woldeyes (2012) reviewed the factors that affect MFI operational and financial sustainability. They are yield on gross loan portfolio; portfolio at risk (PAR); the liquidity ratio (current ratio); the number of borrowers per staff member; cost per borrower; the operating expense ratio; the average disbursed loan size (depth of outreach); size of the MFI; the debt to equity ratio; and the age of the MFI. The author uses a panel regression model and six years of data (2005 to 2010) from the Mix-market database for 12 selected MFIs in Ethiopia. The author identifies four factors that significantly affect MFI operational sustainability: average loan balance per borrower, MFI size, cost per borrower and yield on the gross loan portfolio. Three determinants affect an MFI's financial sustainability: cost per borrower, the number of active borrowers, and yield on the gross loan portfolio. Woldeyes (2012) finds that although MFIs in Ethiopia are operationally self-sufficient, they are not financially self-sufficient. However, Woldeyes' study is limited because it did not include all MFIs in Ethiopia.

Kinde (2012) identifies the determinants that affect Ethiopian MFIs' financial sustainability. The author uses only FSS to represent financial sustainability, following the Mix-market definition. The author uses panel regression and nine years of data (2002 to 2010) from the Mix-market database and The National Bank of Ethiopia for 16 selected Ethiopian MFIs. The author finds that these MFIs are financially self-sufficient and that there are four factors that affect MFI sustainability: microfinance breadth of outreach, depth of outreach, the dependency ratio, and cost per borrower.

Kinde's (2012) results differ from Woldeyes' (2012) because Kinde studied a longer period and used data from two different sources (from both the Mix-market database and the National Bank of Ethiopia), whereas Woldeyes uses only data from the Mix-market database. Secondly, Kinde (2012) evaluated 16 MFIs compared with Woldeyes' 12 MFIs.

Rahman and Mazlan (2014) investigated the determinants that affect FSS of MFIs in Bangladesh. They use multiple regression and independent variables from Woldeyes' (2012) study. Secondary data are from five MFIs in Bangladesh in the Mix-market database between 2005 and 2011. The results show only three factors affect FSS: MFI size, MFI age, and the operating expense ratio.

Some studies use OSS to evaluate financial sustainability (e.g., Bogan, 2012; Quayes, 2012; Sekabira, 2013). Bogan (2012) evaluated how capital structure affects financial sustainability. The author uses OSS to measure financial sustainability and panel data on MFIs in Africa, East Asia, Eastern Europe, Latin America, the Middle East, and South Asia for the years 2003 and 2006. The data are from the Mix-market database. The results show that assets and capital structure affect MFI performance.

Quayes (2012) studied the relationship between the depth of outreach and financial sustainability including OSS and FSS. The author collected data for 2006 from 702 MFIs in 83 countries from the Mix-market database. Quayes finds a positive relationship between the depth of outreach and financial sustainability. Quayes recommends using panel data because they provide scholars with more robust results.

Sekabira (2013) investigated MFI sustainability based on capital structure. OSS and FSS are used to measure MFI sustainability. The author used panel data from 14 Ugandan MFIs (including financial and income statements for five years). Sekabira finds that debt and grants are negatively correlated with OSS and FSS and that capital structure is essential in MFI sustainability.

Previous studies use two indicators to evaluate microfinance institutions' sustainability: OSS and FSS. This study focuses on FSS because it covers the cost of funds and other subsidies. I investigate the determinants that affect the FSS of MFIs in Thailand using panel regression and secondary data, like Kinde (2012) and Woldeyes (2012).

2.6 Chapter Summary

This chapter has reviewed previous studies on household participation in microfinance credit, the impact of participation on economic and social welfare, MFIs' performance and MFIs' sustainability.

To understand the credit market, this study reviewed credit rationing and the demand for credit in the credit market. The asymmetric information problem explains how the credit market works. Asymmetric information flows leads to adverse selection and moral hazard problems. Both problems lead to credit rationing. Credit rationing gives rise to credit constraints regardless of an individual's repayment ability. The demand for credit can explain household behaviours by assuming that households maximize their utility levels. The demand for credit plays an important role in understanding rural households' access to credit.

The first research objective is to investigate factors that affect rural households' access to microfinance programmes. Three main methods have been identified to address this objective: the probit model, the logit model, and the multinomial logit model. This study uses the multinomial logit model because households typically have more than one option for borrowing money. There are also several factors that determine a households' ability to participate in microfinance schemes. These include household head characteristics and demographics (including occupation, income, and assets).

The second objective is to evaluate the impact of microfinance programmes on borrowers' economic and social welfare. Economic welfare consists of income, savings, expenditure, assets, consumption, and investment, whereas social welfare consists of education and healthcare. To address selection bias, this study uses PSM and the fixed effect models to evaluate the impact of microfinance programmes. No studies have evaluated the economic and social welfare impact of microfinance on rural households in Thailand.

The last two objectives investigate MFI performance and sustainability. Previous studies conclude that there are three ways to evaluate MFI performance: outreach, welfare impact, and FSS. This study focuses on FSS. The last objective investigates the factors that affect MFI sustainability. There are two indicators that are typically used to evaluate MFI sustainability: OSS and FSS. This study focuses on FSS. Achieving financial sustainability is important for MFIs. This does not only assure MFIs' existence but also guarantees continued provision of microfinance programmes to the poor. Moreover, no studies evaluate MFI performance and sustainability in Thailand. The next chapter presents and discusses relevant issues in the microfinance literature (the theory of credit rationing, household credit demand, MFI sustainability and performance) to establish the empirical models.

Chapter 3

Research Methodology

The theory of credit rationing, household credit demand, MFI performance and MFI sustainability were introduced in Chapter 2. This chapter expands on them to explain the study's methodology. The chapter is organized into five sections. Section 3.1 discusses the standard assumptions of credit rationing as outlined in Stiglitz and Weiss' (1981) model to explain how imperfect information creates the problem of credit rationing in the credit market. This situation leads to credit constraints. In credit constraint conditions, the demand for credit can be derived using the standard Ramsey Growth Model explained in Section 2.1.3, Chapter 2. The explanation shows how loans can improve individual or household utility through production and consumption and, hence, increase an individual's/household's welfare. Section 3.1 also outlines the empirical model used to investigate the determinants affecting household participation in credit. Section 3.2 describes the Propensity-Score Matching (PSM) and fixed effect (FE) models used to evaluate the impact of microfinance programmes on borrowers' economic and social welfare. Then sections 3.3 and 3.4 discuss the conceptual framework and methodology of MFI financial performance and sustainability. The chapter is summarized in section 3.5.

3.1 Determinants of Credit Participation

3.1.1 The Conceptual Framework

This section links credit rationing and credit demand to explain the poor's participation in credit programmes. This study constructs a model that can be used to explain the credit market under credit rationing conditions. First, borrowers' demands for credit are driven by the borrowers' decisions and household characteristics. Next, the credit supply can be explained by screening procedures, where lenders collect information about the borrower to decide whether to grant the loan application, partially grant it or totally reject it (Zeller, 1994). In a credit constrained condition, household participation in the credit market is defined as the demand for credit (see Stiglitz and Weiss, 1981). Household participation can be defined as when a household has chosen to be a borrower and borrows money (Doan, Gibson & Homes, 2010). Diagne (1999) explains that credit participation relates to borrowers' potential choices and demand for credit. Participation in the credit market is determined by household information, e.g., physical and capital endowments. Some studies have used a reduced form regression equation to investigate the factors that affect credit participation (Diagne, 1999; Doan et al., 2010; Zeller, 1994). Zeller (1994) investigated the factors related to credit rationing in Madagascar and notes that lenders evaluate borrowers using

information from group lenders and the borrowers' creditworthiness. Diagne (1999) evaluated the determinants affecting households' access to credit in Malawi. Diagne finds that a household's total value of assets (land and livestock) determine the poor's access to credit. Investigating the factors affecting Vietnamese access to credit, Doan et al. (2010) conclude that household size, income, phone ownership and the home's location are important factors in determining credit participation.

Borrowers' demands for credit and their creditworthiness are used by lenders to determine whether they will grant loans or not. Therefore, factors determining credit participation can represent either borrowers' demands for credit or borrowers' creditworthiness (Doan et al., 2010). This means if borrowers have more endowments (physical and human resources), they are more likely to be granted (Doan et al., 2010). The factors affecting credit participation are household head characteristics, demographics, occupation, income and assets (Fongthong & Suriya, 2014; Li et al., 2011a; Menkhoff & Rungruxsirivorn, 2011).

Scholars investigating poor households have noted that the above determinants may play other roles in explaining credit participation. These factors may drive credit demand factors rather than the components of creditworthiness. This means that physical endowments (e.g., assets and land ownership) and human endowments (e.g., education) have a negative impact on credit participation (Doan et al., 2010). Evaluating group-lending microfinance programmes and poverty in Bangladesh, Khanker (2005) finds that landless households are more likely to obtain loans from group-lending microfinance programmes than households that own land. The author also finds that education and being female have a negative effect on the number of loans granted from group-lending microfinance programmes. These results suggest that group-lending systems, in which the demand for microfinance is largely derived from landholding eligibility conditions and education, matter in deciding the number of loans from group-lending microfinance programmes (Khanker, 2005). The different factors affecting credit participation for different groups of borrowers are the result of segmented credit markets in developing countries (Doan et al., 2010). Conning and Udry (2007) note that lenders may use diverse ways to screen applicants and evaluate their creditworthiness for different credit segments.

There are also supply-side factors that affect households' participation in credit, e.g., financial lending policies and membership requirements. In short, lenders use diverse methods to screen and evaluate borrowers in different credit segments (Doan et al., 2010). Umoh (2006) points out that many households do not have access to credit because of financial lending policies. These include complicated application procedures, specified minimum loan amounts and prescribed loan purposes. MFIs also have membership requirements, policies on self-selected credit groups and group lending (Li, 2010). Maes and Foose (2006) state that MFIs tend to reject very poor members because they are

unable to repay loans, which destroys the entire group's creditworthiness. These screening methods affect household participation in credit (Li, 2010).

Supply-related and demand-related factors jointly affect households' participation in microfinance programmes. Focusing on the demand side, this study investigates the factors that affect households' participation in MFIs in Thailand. As the literature review has shown, many socio-economic factors affect a household's participation in the credit market. The factors can be divided into four levels: the individual, household, credit market, and geographic levels. The literature tends to focus on the individual level (but not all four levels). Pham and Izumida (2002), Gan, Nartea, and Garay (2007) and Li et al. (2011a) focus on factors at the individual level, including household head age, gender (female), head's ethnicity, and head's education level. The second group (e.g., Chen & Jin, 2017; Gan et al., 2007; Menkhoff & Rungruxsirivorn, 2011; Nguhen, 2007) focuses on household level factors, e.g., land ownership, family size, membership of a credit group, membership requirements, family income and expenditure levels. Pham and Izumida (2002) focus on factors at the credit market level, such as an agricultural loan, trade loan and loan duration. The last group (e.g., Coleman, 1999; Li et al., 2011a; Pill & Khanker, 1988) focus on determinants at the geographic level such as urbanized communes (located in rural areas but adjacent to cities or town where industrial zone(s) are present), road access, and distance to the nearest bank. In this study, factors include borrowers' characteristics, demographic information, occupations, income, and assets like Chen and Jin (2017), Gan et al. (2007), Menkhoff and Rungruxsirivorn (2011) and Nguhen (2007).

3.1.2 Empirical Framework

This study uses discrete choice models (DCMs) to analyse MFI participation in Thailand. DCMs are used to predict and analyse a decision-maker's choice from a set of alternatives, the choice set (Ben-Akiva & Bierlaire, 1999). The choice set has three features that fit within the framework of discrete choices (Ben-Akiva & Bierlaire, 1999; Koppelman & Bhat, 2006; Li, 2010):

1. The alternatives, in the choice set are mutually exclusive. This feature means that if an individual or household chooses one alternative, s/he gives up all other alternatives.
2. The alternatives are collectively exhaustive. This feature means that all the possible alternatives are included in the choice set.
3. The number of alternatives is finite. This means the alternatives can be counted.

DCMs are probability models that are used to specify the probability of a decision-maker making a certain choice, via the utility function (Ben-Akiva & Bierlaire, 1999; Koppelman & Bhat, 2006; Li, 2010). The decision-maker chooses the alternative that maximizes his or her utility. This means that the

borrower chooses the loan/lender based on what provides the greatest utility among the available alternatives in the choice set (C_m) (Ben-Akiva & Bierlaire, 1999; Li, 2010).

To illustrate the decision-maker maximizing his or her utility, let us assume that U_{in} and U_{jn} are the utility that the decision-maker n obtains from alternatives i and j , respectively. The probability that the decision-maker n chooses alternative i from C_m can be shown as (Ben-Akiva & Bierlaire, 1999; Li, 2010):

$$P_n(i|C_m) = Pr[U_{in} > U_{jn}, \forall i, j \in C_m \text{ and } i \neq j] \quad (3.1)$$

To reflect the uncertainty, the utilities of the alternatives are modeled as random variables in DCMs. As a random variable, utility U_{in} is divided into two parts, the systematic part V_{in} and the random components ε_{in} . More specifically, V_{in} is a function related to the observed information. Observed information refers to the decision-maker's characteristics and the alternatives. The random term ε_{in} captures the uncertainty that affects the utility (Ben-Akiva & Bierlaire, 1999; Li, 2010). The utility function is:

$$U_{in} = V_{in} + \varepsilon_{in}, \forall i \in C_m \quad (3.2)$$

$$U_{jn} = V_{jn} + \varepsilon_{jn}, \forall j \in C_m \quad (3.3)$$

Where:

V_{in} , V_{jn} is the deterministic or systematic part of the utility; and

ε_{in} , ε_{jn} is the random term that captures the uncertainty.

The decision-maker chooses an alternative that achieves the highest utility. This means substituting equations (3.2) and (3.3) into equation (3.1). The probability of the decision-maker n choosing alternative i from the choice set C_m can be shown as (Ben-Akiva & Bierlaire, 1999; Li, 2010):

$$P_n(i|C_m) = Pr(U_{in} > U_{jn}) = Pr(V_{in} + \varepsilon_{in} > V_{jn} + \varepsilon_{jn}) \quad (3.4)$$

$$\text{So, } P_n(i|C_m) = Pr(U_{in} > U_{jn}) = Pr(V_{in} - V_{jn} > \varepsilon_{jn} - \varepsilon_{in}) \quad \forall i, j \in C_m \text{ and } i \neq j \quad (3.5)$$

In this study, the choice set contains over two alternatives (multinomial choice). This situation leads to what is termed a multinomial logit model. To formalize this, suppose there is a choice between M alternatives. The alternative i is chosen by individual n if the alternative i gives the highest utility. The probability of choosing alternative i can be shown as (Ben-Akiva & Bierlaire, 1999; Li, 2010; Verbeek, 2008):

$$P_n(i) = Pr(U_{in} = \max\{U_{1n}, U_{2n}, \dots, U_{mn}\}) \quad (3.6)$$

$$\text{So: } P_n(i) = Pr(U_{in} > \max_{k=1, \dots, k, k \neq i} U_{kn}) = Pr(V_{in} + \varepsilon_{in} > \max_{k=1, \dots, k, k \neq i} V_{kn} + \varepsilon_{kn}) \quad (3.7)$$

The multinomial logit model is based on the assumption that the utility error term is mutually independent, which is also known as the type I extreme-value distribution (Verbeek, 2008). Following these assumptions, the distribution function of each ε_{in} , for all i, n can be shown as (Ben-Akiva & Bierlaire, 1999; Maddala, 1994; Verbeek, 2008):

$$F(\varepsilon) = \exp[-e^{-\mu\varepsilon}], \mu > 0 \quad (3.8)$$

Where:

μ : is a positive scale parameter that can be assumed to take the value of 1 for convenience (Ben-Akiva & Bierlaire, 1999).

The probability that a given individual n chooses option i within the choice set C_m is (Ben-Akiva & Bierlaire, 1999):

$$P_n(i) = \frac{e^{\mu V_{in}}}{\sum_{j \in C_m} e^{\mu V_{jn}}} \quad (3.9)$$

Equation (3.9) shows that $P_n(i)$ is a value between 0 and 1 and $\sum_{j \in C_m} e^{\mu V_{jn}} = 1$.

The distribution of the error term in equation (3.9) sets the utility value, which is undefined. To solve this problem, we set one of the deterministic utility levels at zero, $V_{1n} = 0$. This equation is then (Verbeek, 2008):

$$P_n(i) = \frac{e^{\mu V_{in}}}{1 + \sum_{j=2}^m e^{\mu V_{jn}}} \quad (3.10)$$

The systematic part of utility V_{in} is linear in the parameter (Li, 2010):

$$V_{in} = \beta_i X_n \quad (3.11)$$

Where:

β : is a vector of unknown parameters associated with the variables;

X_{in} : is a vector of observed variables relating to alternative i and decision maker n ; and

μ takes the value of 1 for convenience (Ben-Akiva & Bierlaire, 1999).

Adding equation (3.11) into (3.10), the multinomial logit probability, it becomes (Verbeek, 2008):

$$P_n(i) = \frac{e^{\beta_i X_n}}{1 + \sum_{j=2}^m e^{\beta_j X_n}} \quad i=1, 2, \dots, m \quad (3.12)$$

In this study, households choose to participate in microfinance programmes (or not to participate) based on their options; they have more than two mutually exclusive alternatives. The multinomial logit model is used to determine the factors that affect credit participation in Thailand (VFs and SGPs). The model is coded as four outcomes that affect microfinance credit participation (1 = non-VF and SGP borrowing; 2 = borrowing from VFs (only); 3 = borrowing from SGPs (only); 4 = borrowing from both VFs and SGPs).

The choice of microfinance participation in this model depends on household characteristics and the financing strategies that the households chooses to maximize their utility.

If T_{in} is the dependent variable then it can take on one of the different alternative choices.

$P_n(T_n = i)$ is the probability of observing outcome i . The probability model for T_n is (Li, 2010; Verbeek, 2008):

$$P_n(T_n = i) = \frac{e^{\beta_i X_n}}{1 + \sum_{j=2}^4 e^{\beta_j X_n}} \quad (3.13)$$

In other words, the coefficients of the first choice category, which can be arbitrary, are used as a base to compare the alternative choices. In this study, the first choice category, used to compare with the other choices, is the non-borrowing group.

The multinomial logit model can be shown and interpreted in terms of odds. This means the odds of the outcome i versus outcome u (Balogun & Yusuf, 2011; Durojaiye et al., 2014; Mpuga, 2008; Verbeek, 2008) is given as:

$$\frac{P_n(T_n=i)}{P_n(T_n=u)} = \frac{\frac{e^{\beta_i X_n}}{1 + \sum_{j=2}^4 e^{\beta_j X_n}}}{\frac{e^{\beta_u X_n}}{1 + \sum_{j=2}^4 e^{\beta_j X_n}}} = \frac{\exp(X_n \beta_i)}{\exp(X_n \beta_u)} \quad (3.14)$$

Where:

$P_n(T_n = i)$: is the probability of observing outcome i ;

$P_n(T_n = u)$: is the probability of observing outcome u ;

X : is a vector of characteristics including household head characteristics and demographics (including household size, occupation, income and assets); and

β : is the parameter to be estimated.

Arranging the exponent in equation (3.14) leads to the following odds equation:

$$\frac{P_n(T_n=i)}{P_n(T_n=u)} = \exp[X_n(\beta_i - \beta_u)] \quad (3.15)$$

Equation (3.15) shows the odds equation in a non-linear form, which leads to difficulties in interpreting the coefficients. For the purpose of interpretation, equation (3.15) is transformed into a log form. Equation (3.16) expresses the multinomial logit model, which is linear in the logit form (Balogun & Yusuf, 2011; Durojaiye et al., 2014; Mpuga, 2008; Verbeek, 2008):

$$\ln \frac{P_n(T_n=i)}{P_n(T_n=u)} = [X_n(\beta_i - \beta_u)] \quad (3.16)$$

The difference between β_i and β_u in equation (3.16) is the influence of X on the logit of outcome i versus outcome u . This equation can easily compute the partial derivative because the model is linear in logit:

$$\frac{\partial \ln \frac{P_n(T_n=i)}{P_n(T_n=u)}}{\partial X_n} = \frac{\partial X_n(\beta_i - \beta_u)}{\partial X_n} = (\beta_i - \beta_u) \quad (3.17)$$

We can interpret $\beta_i - \beta_u$ in equation (3.17). Thus, holding all other variables constant, changing a unit in X_n , the logit of outcome i versus u will change by $\beta_i - \beta_u$ units.

The multinomial logit models (equations 3.13 – 317) are used to estimate the effect of explanatory variables on the dependent variable, which is an unordered response category. There are two advantages to this model: its computational ease and its relative robustness (Mpuga, 2008).

The multinomial logit model is a nonlinear function of coefficients (β_n). Therefore, the ordinary least squares technique (OLS) cannot be used to estimate this model because it is not statistically appropriate (Li, 2010; Verbeek, 2008). This study therefore uses maximum likelihood estimation (MLE), because MLE can estimate coefficients consistently and asymptotically efficiently (Li, 2010; Verbeek, 2008). MLE consists of model parameters that maximize the probability (or likelihood) of the observed choices, conditional on the model, i.e., it maximizes the likelihood that the sample was generated from the model with the selected parameter values (Koppelman & Bhat, 2006). The likelihood function for a sample of n individuals, each with j alternatives, is defined as (Koppelman & Bhat, 2006):

$$L(\beta) = \prod_{\forall n \in N} \prod_{\forall j \in J} (P_{jn}(\beta))^{\delta_{jn}} \quad (3.18)$$

Where: $\delta_{jn} = 1$ is the chosen indicator (=1 if j is chosen by individual n and 0, otherwise); and

P_{jn} is the probability that individual n chooses alternative j .

The parameter's value that maximizes the likelihood function, is obtained by finding the first derivative of the likelihood function and equating it to zero. This study maximizes the log-likelihood function because the likelihood function and log-likelihood function yield the same maximum and the log-likelihood function is more convenient to differentiate. The function is expressed as (Koppelman & Bhat, 2006):

$$LL(\beta) = \text{Log}(L(\beta)) = \sum_{\forall n \in N} \sum_{\forall j \in J} \delta_{jn} X \ln(P_{jn}(\beta)) \quad (3.19)$$

Therefore, the maximum likelihood estimators $\hat{\beta}$ can be obtained by differentiating equation (3.19) with respect to β_k (Koppelman & Bhat, 2006):

$$\frac{\partial(LL)}{\partial \beta_k} = \sum_{\forall n \in N} \sum_{\forall j \in J} \delta_{jn} X \frac{1}{P_{jn}} X \frac{\partial P_{jn}}{\partial \beta} \quad \forall k \quad (3.20)$$

3.1.3 Explanation of the Variables

The Dependent Variable

The dependent variable for the multinomial logit model is the choice that an individual or household i makes. The dependent variable has four outcomes that affect microfinance credit participation (1 = non-VF and SGP borrowing; 2 = borrowing from VFs (only); 3 = borrowing from SGPs (only); 4 = borrowing from both VFs and SGPs). Microfinance credit participation means that the borrower decides to accept a loan from a microfinance programme (Diagne, 1999).

Independent Variables

Table 3.1 shows the independent variables used in the multinomial logit model.

Table 3.1 Description of Variables used in the Multinomial Logit Model

Variable Name	Description	Measures
(a) Borrower Characteristics:		
Age	The borrower's age	years
Gender	The borrower's gender	1=female; 0=male
Education	The borrower's education level	years
Marital Status	The borrower's marital status	1=married, 0=otherwise
(b) Demographics:		
Household Size	Number of persons	persons
Dependency Ratio	This is defined as the ratio of non-workers to workers in each household	persons
(C) Occupation:		
Landless Farmers	Farmers do not have their own land	1=landless farmer, 0=otherwise
Farmers	Borrowers are farmers	1=farmer, 0=otherwise

Variable Name	Description	Measures
Entrepreneurs	Borrowers are entrepreneurs	1=entrepreneur, 0=otherwise
Formal Workers	Borrowers are formal workers	1=formal workers, 0=otherwise
Informal Workers	Borrowers are informal workers	1=informal worker, 0=otherwise
Unemployed	Borrowers are unemployed	1=unemployed, 0=otherwise
(d) Income and Assets		
Monthly Income	Monthly household income	THB 1,000
Assets	Total value of household assets	THB 1,000

The hypothesized relationship between the independent variables and household participation in microfinance programmes in Thailand is based on previous studies. Education (+) means that the education of the borrower is positively related to participation in microfinance programmes. The borrower's education reflects human capital, which facilitates participation in microfinance programmes. Mpuga (2008) notes that educated borrowers are more likely to have higher income and savings and therefore are more likely to have assets that can be used as collateral. Li (2010) states that educated farmers can better understand the conditions of microfinance loans and they are more likely to comply with microfinance loan requirements.

Borrower characteristics affecting participation in microfinance programmes are age, gender and marital status. Age and gender are hypothesized to negatively influence participation, whereas marital status is hypothesized to positively influence access to the programmes. Generally, younger individuals are more energetic and dynamic, meaning they adopt new technologies better than older individuals. Therefore, young individuals tend to save and/or borrow more for investment, whereas older individuals may be less inclined to save or borrow (Li, 2010; Mpuga, 2008). Li (2010) states that older individuals struggle to understand the operations and loan conditions and therefore do not tend to participate in microfinance schemes. Mohamed (2003) and Okurut (2006) confirm that the probability of borrowing from formal and semi-formal sources of credit reduces for older individuals. In terms of gender, it is hypothesized that female borrowers are more disadvantaged in securing microfinance loans than men because, in the rural areas, women have limited access to information and information technologies, in particular. Women's limited freedom and mobility leads to decreasing demands for credit, thus decreasing the likelihood of microfinance participation (Evans, Adams, & Mohammed, 1999; Li, 2010; Zeller, 1994). Marital status is hypothesized to positively influence household access to microfinance programmes because married people are more likely to be stable and lenders view them as more reliable. Therefore they are more likely to access credit than their unmarried counterparts (Mpuga, 2008).

In terms of occupation, the farmer and entrepreneur variables are hypothesized to positively affect participation in credit facilities, whereas the landless farmers, formal and informal workers, and

unemployed variables are hypothesized to negatively affect participation in microfinance programmes. Borrowers who operate a business in addition to agricultural production have a higher probability of participating in microfinance programmes because they need financial support to invest in or expand their businesses (Li, 2010; Mohamed, 2003).

The dependency ratio is defined as the ratio of non-workers to workers in each household (Fongthong & Suriya, 2014). A higher ratio reduces a household's ability to repay credit and thus the probability of these households' participation in microfinance programmes is lower.

Some variables (such as household size, income and assets), have ambiguous relationships with household participation in microfinance programmes. The ambiguous effects of these variables on households' participation in microfinance programmes arise from their uncertain effects on households' demand for credit (Li, 2010). An example of the uncertainty effects relates to family size. Larger households tend to have greater levels of consumption thus they often have greater credit demands. However, a larger household size also means that they are less likely to meet repayment requirements because they have a smaller future expected income, which reduces the demand for credit (Li, 2010; Nguyen, 2007; Ruiz-Tagle, 2005). Similarly, income and assets have an uncertain effect. When households have more income and/or assets, they feel rich and consume more. Therefore, they may also demand more credit (Cheng, 2006; Li, 2010; Ruiz-Tagle, 2005). However, income and assets show a household's initial capital. This means a higher level of income and/or assets reflect a less constrained household budget, which may weaken the demand for credit (Li, 2010; Ruiz-Tagle, 2005; Umoh, 2006).

To investigate the factors that impact microfinance programmes, this study uses cross-sectional data from the Socioeconomic Survey (2017), collected by the National Statistical Office of The Ministry of Information and Communication Technology in 2017. The survey interviewed 43,210 households across the country. Data were collected on a monthly basis, including a variety of household socioeconomic data such as household basics, covering income, expenses, assets, and liabilities.

This study links credit rationing and the demand for credit, to explain households' participation in the credit market. The credit rationing model explains how imperfect information leads to the problem of credit rationing in the credit market. This situation leads to credit constraints. The model assumes that the credit market is characterised by asymmetric information. The model shows a household's decision in the credit market. Households desire to maximise their satisfaction levels via consumption, even under credit constraints. An individual launches a project or investment if the expected return, in the case of success, is greater than the opportunity cost, which refers to the individual borrower's initial wealth. Households can choose to borrow from a variety of sources, but often choose the alternatives that will maximize his/her utility. The multinomial logit model is used

to determine the determinants that affect credit participation in two Thai MFIs (VFs and SGPs). We use this model because households have more than two alternative credit sources. This model is known for its computational ease and is considered relatively robust, as measured by the goodness of fit and prediction accuracy tests (Mpuga, 2008).

3.2 Impact Evaluation of Microfinance Programmes on the Economic and Social Welfare of Thai Households

In this study, microfinance impact evaluation consists of two parts: the welfare outcome of impact evaluation and an empirical model. The first part evaluates the impact of particular microfinance programmes using welfare outcome indicators. In the second part, the empirical model explains how PSM and fixed effect models are used to evaluate the impact of VFs and SGPs on borrowers' economic and social welfare.

3.2.1 Welfare Outcomes of Impact Evaluation

The main objective of impact evaluation of microfinance is to evaluate the differences between agents' outcomes (e.g., individuals, households, firms, and cities) that participate in intervention programmes, against outcomes that would have occurred without any programmes/participation. Coleman (2006) concludes that microfinance impacts can be divided into two parts: the impact on economic welfare and on social welfare. In terms of the economic welfare impact of microfinance, two common indicators are used: income and consumption (Hume, 2000). Income indicators are calculated using all sources of income. These indicators are included to evaluate the impact of microfinance programmes. However, the welfare impact measurement from household income may be misleading because of errors in income data (Li, 2010; Phan, 2012). Household income tends to fluctuate during the year because of the dependence on agricultural production and natural conditions. This means that household income is difficult to measure or predict. Furthermore, some households wrongly estimate their income, e.g., if a large proportion of income is not monetarized. If households consume their own products or exchange their production for other goods, this situation leads to households underestimating their total income (Islam, 2007; Li, 2010; Phan, 2012). Consumption is more stable than income during a household's lifetime. It can better reflect a household's actual living standard and shows its ability to meet its basic needs (Islam, 2007; Li, 2010; Phan, 2012).

Several studies focus on economic welfare (e.g., Burgess & Pande, 2002; Chandoevmit & Ashakul, 2008; Khandker & Faruquee, 2003). Khandker and Faruquee (2003) studied the impact of farm credit on household welfare in Pakistan. The authors find that loans contribute positively to household welfare and that the impact on consumption and production is higher for smallholders than for large holders.

Burgess and Pande (2002) evaluated the impact of rural banks on poverty reduction in India. They find that rural banks significantly affect economic growth and total per capita output. Rural banks also impact small-scale manufacturing. The services most impacted by the existence of rural banks are non-agricultural outputs. The authors also find that rural poverty reduction is linked to expanded savings mobilization and credit provisions in rural areas. They conclude that the poor take loans to improve capital accumulation and long-term productive investments.

Chandoevrit and Ashakul (2008) investigated the impact of the VF on Thai household income, expenditure and the incidence of poverty. Their results show that the VF has not alleviated the country's poverty. The VF increases farm income only in the central region and non-consumption expenditure in the northern and southern regions. The increase in non-consumption expenditure suggests that borrowers in the northern and southern regions do not spend their loans on investments. The authors conclude that the VF alone cannot alleviate poverty. They also suggest that VF loans should provide borrowers with information about investment channels, risk management, and technical knowledge.

Some studies evaluated the impact of microfinance on both economic and social welfare (e.g., Aktaruzzaman & Farooq, 2016; Cintina & Love, 2014; Coleman, 2006). Coleman (2006) evaluated the impact of microfinance programmes on both the economic and social welfare of households in Thailand. Coleman states that village banks positively affect committee members' households at the expense of poorer borrowers. Focusing on medical and school expenditure, Coleman shows that village banks do not impact borrowers' medical and school expenditure. This study also shows that educational expenditure for boys by committee members' households is significantly higher than for boys in poorer member households.

Cintina and Love (2014) compared microfinance programmes' impact on borrowers' expenditure in India. They find that microfinance borrowers exhibit higher expenditure in several categories: durables, house repairs, health, festivals and temptation goods. Aktaruzzaman and Farooq (2016) examined the impact of participation in microcredit programmes on consumption in Bangladesh. The authors find that access to the programmes decreased per capita expenditure on durable goods while increasing expenditure on each school-going child as well as non-durable goods and healthcare, recreation and gifts.

Some studies focus on poverty (e.g., Cuong, 2008; Swain & Floro, 2012). Cuong (2008) evaluated programmes that actually reach the poor and the impact of microcredit programmes in Vietnam. The author finds that microcredit programmes are not very pro-poor. Cuong states that most borrowers are not poor and that this group of borrowers receives more loans than the poor. However, the programme reduces participants' poverty rate. Cuong finds that borrowers in the programme have

greater incomes and higher consumption levels. Swain and Floro (2012) investigated whether the Self Help Group (SHG) in India reduces borrowers' poverty and household vulnerability. Their results show that SHG members' vulnerability is not significantly higher than non-SHG members. However, SHG members' vulnerability reduces significantly after more than one year. This result suggests that the impact of SHG on vulnerability takes longer.

This study evaluates the impact of microfinance programmes on both economic and social welfare. First, it examines the impact of microfinance programmes on economic welfare, including consumption. Consumption covers both food and non-food items, whereas income refers to the sum of all possible sources of finance in a household. This study also includes the impact of microfinance programmes on borrowers' social welfare such as medical and school expenditure. As Kasali et al. (2016) note, microfinance loans are used primarily for health, education and production and are given as aid for recovery efforts from events like natural disaster and health-related calamities.

3.2.2 Empirical Model

The aim of impact assessment is to compare differences in outcomes, in terms of individual or household income and consumption. Instead of using different agents, impact assessment estimates differences in outcomes for the same agents, i.e., with aid and without it. In this study, T_i is a binary variable that shows microfinance participation. If T_i equals one, it means an individual or household i participates in a microfinance programme. If T_i equals zero, it means an individual or household i does not participate in any microfinance programme. We also assume Y_{i1} shows the outcome value of interest when an individual or household i participates in a microfinance programme. Y_{i0} shows the outcome value of interest when an individual or household i does not participate in a microfinance programme.

The impact of the microfinance on the outcome of the i_{th} individual or household can be measured by:

$$\Delta i = y_{i1} - y_{i0} \quad (3.21)$$

The impact identified in equation (3.21) is equal to the difference in outcomes when an individual or household participates in a microfinance programme to the same outcomes when s/he does not participate in a microfinance programme. The outcomes cannot be observed because the same household or individual cannot participate or not participate at the same time. This problem is called a counterfactual problem (Heckman et al., 1997). Therefore, a microfinance programme's impact cannot be estimated because of the counterfactual problem. As Kono and Takahashi (2010) and Stuart (2010) note, ATT is commonly used to evaluate microfinance programme impacts because these methods can directly measure the microfinance programme impact on the target group.

ATT measures the impact of programme participation on individuals or households that participate in the programme (Kono & Takahashi, 2010). ATT can be shown as (Li, 2010; Phan, 2012):

$$\delta_i = E(y_{i1} | T_i=1) - E(y_{i0} | T_i=1) \quad (3.22)$$

Assuming δ_i is the true impact of microfinance programmes and the study can observe both y_{i1} and y_{i0} for any individual or household, the average difference in outcome should be attributable to access to microfinance programmes. If $E(y_{i1} | T_i=1) - E(y_{i0} | T_i=1)$ are positive, it can be shown that microfinance programmes have a positive impact on the outcome of interest and vice versa.

However, the ATT method cannot be estimated directly because some components in equation (3.22) cannot be directly observed. This means we can estimate $E(y_{i1} | T_i=1)$, but we cannot estimate $E(y_{i0} | T_i=1)$. This problem can be addressed by constructing counterfactuals based on the treatment and control framework (Li, 2010). The idea of this framework is to select non-participation in the programme as a control group and observe the outcomes of this group. Based on this idea, we can evaluate the impact of microfinance as (Li, 2010; Phan, 2012):

$$\delta^* = E(y_{i1} | T_i=1) - E(y_{j0} | T_j=0) \quad (3.23)$$

In equation (3.23), δ^* is the estimation of the true impact of microfinance programmes. We can estimate the outcome of microfinance programmes using two different individuals or households; individual or household i participates in the microfinance programmes and individual or household j does not. y_{i1} is the outcome evaluated for individual or household i and y_{j1} is the same outcome evaluated for individual or household j . This study evaluates the impact of microfinance programmes on the economic and social welfare of individuals or households using the ATT method. In the next section, we discuss two types of programme impact estimators used to investigate the effect of microfinance programmes.

3.2.2.1 Propensity Score Matching Method

Propensity score matching (PSM) is a method that attempts to find a comparison group; this group is very similar to the treatment group except for the treatment status (Kono & Takahashi, 2010). The similarity between the two groups is evaluated by observable characteristics. This method compares the outcome of the treatment group with the outcome of the comparison group (Phan, 2012). This means differences in outcomes between the two groups can be attributed to the programme of interest (Heckman et al., 1997). This approach is typically used to evaluate the impact of job training and education programmes (Dehejia & Wahba, 2002).

Several scholars have used the matching model to evaluate microfinance impact (e.g., Cintina & Love, 2014; Setboonsarng & Parpiev, 2008; Swain & Floro, 2012). Setboonsarng and Parpiev (2008) studied

the impact of the Khushhali Bank (KB) in Pakistan, using the PSM method to address selection bias. They find that KB contributes significantly, positively to income generation activities, but has a minimal effect on education, health and female empowerment. The authors conclude that the microfinance programme contributes to income generation, providing children with school education and training, and access to health services.

Swain and Floro (2012) investigated the Self Help Group (SHG) in India. This programme is designed to reduce poverty and household vulnerability. The authors use PSM and linear regression to evaluate the impact of the microfinance programme. Their results show that microfinance members' vulnerability is not significantly higher than non-microfinance members. However, members' vulnerability reduces significantly after more than a year.

Cintina and Love (2014) compared microfinance borrowers' expenditure using the PSM method to determine its impact. They find that microfinance borrowers exhibit higher expenditure. The results suggest that microfinance programmes make a notable difference to borrower expenditure. However, this increased expenditure does not lead to long-term benefits because the loans are likely to be unproductive expenditure; in short, they improve utility in the short term but are unlikely to lead to any significant long term changes.

In this study, PSM is used to measure microfinance programmes' impact on borrowers' economic and social welfare in Thailand (only of those who participate in the scheme). This method can be used to estimate the propensity scores for each borrower and non-borrower in a microfinance programme based on observed characteristics such as age, gender, education, and land holding status. It compares the mean outcome of the borrowers with that of the matched (similar in terms of scores) non-borrowers (Kono & Takahashi, 2010).

PSM is the conditional probability of receiving a treatment given X (Arun, Imai & Sinha, 2006).

$$p(X) = Pr\{T = 1|X\} = E\{T|X\} \quad (3.24)$$

Where:

$T = \{0,1\}$: a binary variable if an individual or household has participated in a microfinance programme ($T=1$) or if not ($T=0$); and

X : is a vector of pre-treatment characteristics.

Three assumptions underpin PSM for the identification of the programme effect: the assumption of conditional independence, common support and mean dependence.

a. Assumption of Conditional Independence

PSM depends on the assumption of conditional independence, which is conditional on the observed characteristics. This assumption means that participation in the microfinance programme is independent of the outcome of interest. This assumption can be shown as (Kono & Takahashi, 2010; Phan, 2012):

$$(y_0, y_1) \perp\!\!\!\perp T|x \text{ for all ATE} \quad (3.25a)$$

$$y_0 \perp\!\!\!\perp T|x \text{ for all ATT} \quad (3.25b)$$

Where:

x : is a set of observed characteristics;

y_0 : is the outcomes for non-participants;

y_1 : is the outcomes for participants;

ATE: is the Average Treatment Effect; and

ATT: is the Average Treatment Effect on the Treated.

Equations (3.25a) and (3.25b) imply that the outcome distributions of participants and non-participants can be defined as (Kono & Takahashi, 2010; Phan, 2012):

$$E(y_0|x, T = 1) = E(y_0|x, T = 0) = E(y_0|x) \quad (3.26a)$$

$$E(y_1|x, T = 1) = E(y_1|x, T = 0) = E(y_1|x) \quad (3.26b)$$

Equations (3.26a) and (3.26b) imply that the outcomes for participants are similar to those of non-participants, if both groups are in the same situation.

If both sides of equations (3.26a) and (3.26b) are simultaneously defined for all x , PSM can add the assumption of common support.

b. Assumption of Common Support

The second assumption can be shown as (Khandker et al., 2010):

$$0 < Pr(T = 1|x) < 1, \text{ for all } x \quad (3.27)$$

Equation (3.27) shows a significant overlap in covariate x between the treatment and comparison groups. This means that individuals with the same observed characteristics (x) have a positive

probability of being both participants and non-participants in the microfinance programme (Kono & Takahashi, 2010). Thus, the second assumption implies that the support for x is equal in both groups (participants and non-participants). For example, $S = \text{Support}(x | T=1) = \text{Support}(x | T=0)$ which means the matched pairs of the treatment and comparison groups, over the region of common support, have the same propensity scores. Next, we calculate the average of the difference between the matched treatment and comparison groups. This calculation can be treated as the impact of microfinance programmes (Kono & Takahashi, 2010). If the region in which the support of x does not overlap for the treatment and comparison groups, matching is performed only over the common support region (Lechner, 2000). This means that interpretation of microfinance impact has to be redefined as the mean treatment effect of those individual or household that fall within the common support (Blundell, Dearden & Sianesi, 2005).

Rosenbaum and Rubin (1983) note that the first and second assumptions can be called “strong ignorability” in practice. Strong ignorability implies that the balancing scores indicate the distributions of covariates between the treatment and comparison groups are the same (Rosenbaum & Rubin, 1983). That means if treatment assignment is strongly ignorable, then the difference between the treatment and comparison groups at each value of a balancing score is an unbiased estimation of the treatment effect. Moreover, pair matching, sub-classification and covariance adjustment on a balancing score can produce an unbiased estimate of ATE (Rosenbaum & Rubin, 1983).

Heckman et al. (1997) provide an alternative assumption to estimate ATT under the matching method.

c. Mean Independence

$$E(y_0|T = 1, x) = E(y_0|T = 0, x) = E(y_0|x) \text{ and } E(y_1|T = 1, x) = E(y_1|T = 0, x) = E(y_1|x)$$

Based on the above assumptions, the mean impact of the treatment on the treated can be shown as (Kono & Takahashi, 2010; Phan, 2012):

$$\delta_{PSM}^{ATT} = E(y_1|T = 1, x) - E(y_0|T = 1, x) \quad (3.28a)$$

$$\delta_{PSM}^{ATT} = [E(y_1|T = 1, x) - E(y_0|T = 0, x)] - [E(y_0|T = 1, x) - E(y_0|T = 0, x)] \quad (3.28b)$$

$$\delta_{PSM}^{ATT} = E(y_1|T = 1, x) - E(y_0|T = 0, x) \quad (3.28c)$$

Where:

y_1, y_0 : are the potential outcomes in the two counterfactual situations (i.e., participation in the microfinance programme and no participation in the microfinance programme).

The first line in equation (3.28a) shows the policy effect. The effect is defined by the difference between the economic and social indicators of households participating in the microfinance programme and for the same household in the counterfactual that does not participate in the microfinance programme. Based on $E(y_0|T = 1, x) = E(y_0|T = 0, x)$, ATT can be estimated consistently if unobserved characteristics of households are not important factors of selection for participation in microfinance programme (Kono & Takahashi, 2010).

However, Marr (2012) argues that PSM cannot control for unobserved characteristics that affect microfinance participation. Moreover, the method is suitable only for cross-sectional survey data (Dehejia & Wahba, 2002). Nguyen (2007) notes concerns about the bias in microfinance impact assessment using PSM and cross-sectional data. The author proposes using panel data with PSM and the fixed effect models to solve this problem. Phan et al. (2013) deal with this problem using panel data and estimate PSM in the first period to match borrowers and non-borrowers using a set of observed characteristics. In the first stage, PSM creates a new data set consisting of borrower and non-borrower groups that are more comparable in terms of observed characteristics than the original panel data. The purpose of this step is to remove observed heterogeneity in the first period before using the fixed effect model to investigate the impact of microfinance programmes (Heckman et al., 1997). Phan et al. (2013) conclude that PSM and the fixed effect model can solve observed and unobserved biases. The next section explains how the fixed effect model works.

3.2.2.2 The Fixed Effect Model

Panel data are used to solve the unobserved variable bias when measuring the impact of VFs and SGPs (Boonperm et al., 2013). This study uses panel data and the fixed effect (FE) model to evaluate the impact of VFs and SGPs in Thailand. There are some advantages to using a FE model. First, the model can control for relevant unobserved characteristics that do not change over time (Lensink & Pham 2008). Secondly, the FE model also allows observed characteristics to be arbitrarily correlated with unobserved fixed effects. This means that the estimates in this model are robust (Wooldridge, 2009). However, there are some factors that are time-constant (e.g., gender). These factors cannot be included in this model because we cannot distinguish the effects of time-constant factors from unobserved fixed effects or if unobserved fixed effects can be arbitrarily correlated with regressors (Wooldridge, 2009). Although this model can control unobserved time-invariant attributes, it does not entirely control the endogeneity problem¹ that comes from unobserved attributes that may change over time (Khandekar, 2005). It is necessary to test for endogeneity to detect whether the FE method is sufficient to determine the exogenous programme impact or if instrument variables (IVs)

¹ Endogeneity is likely to occur if the assumption of unobserved factors at household, village and community levels does not remain fixed. Probable sources of endogeneity in this study include, a change in lending regulations that might affect microfinance participation and a household's income and expenditure.

are need for the identification of the endogenous programme impact (Khandekar, 2005; Phan et al., 2013). To overcome the problem of endogeneity, this study could use village poverty rates and the distance from the village to the nearest MFIs as IVs; however, this information is not available. This study uses Boonperm et al.'s (2013) model:

$$y_{it} = \alpha_i + X_{it}\beta + T_{it}\gamma + YEAR_t\phi + \varepsilon_{it} \quad (3.29)$$

Where y_{it} indicates the outcome variables of interest, e.g., household income and consumption for household i at time t ($t= 2012, 2017$), X_{it} is a set of regressors that are the observed household characteristics, such as household head's gender, household head's age, number of household members, education level, careers, value of house and land holding, T_{it} is a programme participation dummy variable that takes the value of 1 if individual or household i takes a loan from microfinance programme in time t and 0 otherwise. $YEAR_t$ is a vector of year dummy that considers time-specific effects, α_i indicates unobserved characteristic of the household and ε_{it} is an error term.

A fixed effect model sets a separate intercept (α_i) for each household to eliminate (unobserved) heterogeneity across households. The model is given in equation (3.30):

$$y_{it} - y_{it-1} = (X_{it} - X_{it-1})\beta + (T_{it} - T_{it-1})\gamma + (YEAR_t - YEAR_{t-1})\phi + (\varepsilon_{it} - \varepsilon_{it-1}) \quad (3.30)$$

This study estimates the impact of VFs and SGPs on VFs' and SGPs borrowers' economic and social welfare using equation (3.30). The model generates within estimates that are identified by variation over time whether a household borrows from the VFs or SGPs. This study uses secondary data from Thailand's Socioeconomic Survey (2012 and 2017) collected by the National Statistical Office of the Ministry of Information and Communication Technology. The survey interviewed 6,000 households across the country. Data were collected monthly. The information includes a variety of household socioeconomic data, such as household basics, covering income, expenses, assets, and liabilities. It is important to use data from both 2012 and 2017 to evaluate the impact of microfinance borrowing, because the impact of microfinance borrowing in equation (3.30) comes from a change in borrowing habits in variable T_{it} . Therefore, we cannot estimate the impact of microfinance programmes, y , if borrowing habits do not change (Boonperm et al., 2013). This means that if a borrower takes a loan one year and another year does not borrow or vice versa, we can still estimate the impact of microfinance programmes.

In summary, this study uses both the PSM and the fixed effect methods because they can solve observed and unobserved biases. PSM is estimated for the first time to match borrowers with non-borrowers, using a set of observable characteristics. This method is used to create a new panel data

set that consists of borrower and non-borrower groups with similar observed characteristics. The objective of this step is to eradicate the observed heterogeneity in the initial period before using the fixed effect model (Heckman et al., 1997).

3.3 MFIs' Performance

This section explains the conceptual framework and methodology used to investigate MFIs' performance.

3.3.1 Conceptual Framework

This study focuses on institutional characteristics: outreach, productivity, and financial performance of MFIs in Thailand. The institutional characteristics provide us with a picture of an individual MFI. This study includes MFI age, the number of personnel, profit, total assets, total liabilities and total equity. An MFI's age is associated with experience. Shahzad (2015) evaluated South Asian MFIs' performance and finds that older MFIs are more efficient than younger MFIs. Hermes et al. (2008) argue that MFI age indicates the number of years since its establishment and older MFIs can learn how to manage their MFIs with microfinance practices by trial and error. Kar (2012) states that older MFIs may benefit from organizational learning. Therefore, in this study, MFI age is hypothesized to affect MIF performance.

The number of personnel refers to the total number of staff members; the more staff members an MFI has, the larger an MFI is. MFIs that have more staff are more capable of serving and keeping track of a larger number of borrowers (El-Maksoud, 2016). El-Maksoud (2016) notes that larger MFIs can hire more staff and open new branches, which means that they are more capable of reaching more borrowers. Anduanbessa (2009) evaluated Ethiopian MFIs' performance and finds that the number of staff members affects MFI outreach.

MFI profit shows the profit, which reflects an MFI's ability to cover its costs with its revenue, without accounting for implicit grants and subsidies (Cull, Demirguc-Kunt, & Morduch, 2016, 2018). Sustainability means that an MFI is financially viable into the future (Shaoyan & Duwal, 2012). This indicates that an MFI should generate sufficient profit to cover its expenses while eliminating all subsidies. Dissanayake (2012) points out that MFIs must be well designed to be profitable and alleviate poverty.

MFI assets show the MFI's size. Larger MFIs can benefit from economies of scale by reducing operating expenses and therefore achieving greater financial performance (Meyer, 2019). MFI assets are associated with MFI's FSS (Mersland & Storm, 2009). Greater assets can imply that an MFI has

more capital; thus larger MFIs can reach greater numbers of people than smaller MFIs (Mersland & Storm, 2009).

The term total liabilities refers to all liability accounts, which represent everything that an MFI owes to others (CGAP, 2003). Total liabilities include all deposits, borrowings, accounts payable, and other liability accounts (CGAP, 2003). When MFIs take on more debt instruments, efficient liability management and planning is key to growing the institutions (Bayai & Ikhida, 2016). Muriu (2011) states that if MFIs employ more debt in their capital structure, these institutions can increase their profits. However, Dissanayake (2012) finds that total liabilities do not affect an MFI's performance. Kar (2012) explains that long-term debts are more expensive and, therefore, employing a high proportion of these debts could lead to lower profitability.

Total equity covers total assets once total liabilities have been deducted (CGAP, 2003). Total equity is the sum of all equity accounts net equity distributions, e.g., dividends, stock repurchases, or other cash payments made to shareholders (CGAP, 2003). Kar (2012) states that capital structure has an impact on MFI performance. Bayai and Ikhida (2016) point out that equity is cheap and can increase an MFI's FSS.

Outreach efforts demonstrate an MFI's ability to reach the poor and ensure the efficient use of funds. MFI outreach can be evaluated using two aspects: depth of outreach and breadth of outreach (Ngo, 2012). The depth of outreach refers to borrowers' poverty and the breadth of outreach refers to the scale of an MFI's operations (Ngo, 2012). Almost all MFIs' core aim is to expand outreach. The most common indicators used to measure outreach are average loan balance per borrower and number of active borrowers, representing the depth and breadth of outreach (Bhuiyan et al., 2011; Ngo, 2012).

Productivity refers to the volume of business that is generated (output) for any given resource or asset (input) (Ledgerwood, 1998). Several ratios are commonly used to evaluate MFI productivity. These ratios focus on MFI staff productivity because they are the primary revenue generators. This study uses average loan balance per borrower, borrowers per staff member, and loans per staff member, which are like Bhuiyan et al.'s (2011) and Rahman and Mazlan's (2014) studies.

The financial performance of MFIs can be evaluated using two indicators: financial structure and financial performance (Rahman & Mazlan, 2014). Financial structure includes five factors: capital per asset, debt per equity, deposit per loans, deposit per total assets, and gross loan portfolio per assets. Financial performance is whether an MFI is profitable enough to maintain and expand its services without subsidies (Rosenberg, 2009). Financial performance covers three indicators: ROE shows

institutional profitability; ROA is institutional profitability that reflects both the institutional profit margin and institutional efficiency; OSS measures how well an MFI can cover its costs.

Some studies use two indicators (financial structure and financial performance) to evaluate MFIs (e.g., Agarwal & Sinha, 2010; Bhuiyan et al., 2011; Rahman & Mazlan, 2014). Agarwal and Sinha (2010) evaluated MFI performance using six parameters of financial performance: financial structure; revenue; expenses; efficiency; productivity; and risk. The author finds that in India the best performing firms follow different business models. This result is reflected in particular parameters such as the capital per asset ratio, deposits to loans, deposits to total assets, gross loan portfolio per total assets and ROA. Bhuiyan et al. (2011) compared financial sustainability and outreach between MFIs in Malaysia and Bangladesh using the same indicators as Agarwal and Sinha (2010) and indicators that show MFI outreach. Their results show that Malaysian MFIs perform better than those in Bangladesh in terms of operational self-sufficiency, earning revenue and financial expenses. The authors show that Malaysian MFIs have lower expenses than Bangladeshi MFIs. However, Malaysian MFIs' performance is lower in terms of outreach. Malaysian MFIs have lower performance levels in terms of active borrowers, the number of the loans outstanding, and gross loan portfolios. Bhuiyan et al. (2011) suggest that MFIs in Malaysia should adopt Islamic microfinance principles because they deal with poor people. Rahman and Mazlan (2014) compared the financial performance of five MFIs in Bangladesh. The authors used the performance indicators financial structure and financial performance. These indicators consist of the capital assets ratio; debt to equity; deposit to loans; deposits to total assets; gross loan portfolio to assets; ROA; ROE; OSS. They find that all MFIs are financially sustainable because all of them exhibit positive values for both ROE and ROA.

This study compares the institutional characteristics, outreach, productivity, financial structure and financial performance of VFs and SGPs in Thailand using the performance indicators and ratios shown in Table 3.2. There are five ratios in financial structure: the capital per asset ratio; debt per equity (%); deposit per loans (%); deposits per total assets (%); gross loan portfolio per assets (%). The capital per asset ratio is used to evaluate MFI solvency. This variable also shows an MFI's ability to meet its obligations and absorb unexpected losses (Yenesew, 2014). Yenesew (2014) states that the determination of an acceptable ratio level is generally based on an MFI assessment: expected losses; financial strength; and ability to absorb losses. This means that the ratio measures the amount of capital required to cover unexpected losses. This study uses capital per asset ratio as a proxy for MFIs' capital. That means if an MFI has higher capital per asset ratio, this MFI is safer than lower ratio institutions. Agarwal and Sinha (2010) evaluated MFIs performance in India. The authors find that the capital per asset ratio shows that MFIs in India are different in terms of their risk management practices because Indian MFIs maintain divergent capital per asset ratios. However, Agarwal and

Sinha (2010) do not explain why MFIs do this. Bhuiyan et al. (2011) compared MFI financial sustainability and outreach in Malaysia and Bangladesh. They find that the capital per asset ratio of MFIs in Malaysia is lower than that in Bangladesh; the capital per asset ratio of MFIs in Malaysia is 15.4, whereas in Bangladesh it is 23.9. However, Bhuiyan et al. (2011) do not explain why the capital per asset ratio of MFIs in Malaysia is lower than in Bangladesh.

Table 3.2 Institutional Characteristics, Outreach, Productivity, Financial Performance Measurement Indicators and Ratios

Indicator	Ratio or Calculation
1. Institutional Characteristics	
Age (years)	Age of MFI
Personnel (Persons)	Number of Personnel
Profit	MFI's Profit
Total Assets	Total Assets of MFI
Total Liability	Total Liability of MFI
Total Equity	Total Equity of MFI
2. Outreach	
The Number of Members (persons)	Number of Members
The Number of Borrowers (Persons)	Number of Borrowers
Average Loan Balance per Borrower (Baht per Borrower)	$\frac{\text{Gross Loan Portfolio}}{\text{Number of Active Borrowers}}$
3. Productivity	
Borrowers per Staff Member	$\frac{\text{Number of Active Borrowers}}{\text{Number of Personnel}}$
Loans per Staff Member	$\frac{\text{Gross Loan Portfolio}}{\text{Number of Personnel}}$
4. Financial Structure	
Capital per Asset Ratio	$\frac{\text{Equity}}{\text{Assets}}$
Debt per Equity (%)	$\frac{\text{Liabilities}}{\text{Equity}}$
Deposit per Loan (%)	$\frac{\text{Deposits}}{\text{Gross Loan Portfolio}}$
Deposits per Total Assets (%)	$\frac{\text{Deposits}}{\text{Assets}}$
Gross Loan Portfolio per Assets (%)	$\frac{\text{Gross Loan Portfolio}}{\text{Assets}}$
5. Financial Performance	
ROA	$\frac{(\text{Net Operating Income} - \text{Taxes})}{\text{Average Total Assets}}$
ROE	$\frac{(\text{Net Operating Income} - \text{Taxes})}{\text{Average Total Equity}}$
OSS	$\frac{\text{Financial Revenue}}{(\text{Financial Expense} + \text{Net Impairment} + \text{Operating Expense})}$

Source: Bhuiyan et al. (2011); Rahman, and Mazlan (2014)

The debt per equity ratio is measured by dividing total liability by total equity. Total liability includes all the debt that an MFI owes, such as deposits, borrowings, and other liability accounts. This ratio is the simplest indication of capital adequacy because the ratio reflects an MFI's overall leverage (Yenesew, 2014). Muriu (2011) evaluated MFIs' profitability in 32 countries. The author asserts that if MFIs employ more debt in their capital structure, these institutions can increase their profits. Muriu also shows that a higher debt per equity ratio can improve ROE. Dissanayake (2012) investigated the factors affecting MFIs' profitability in Sri Lanka. The author finds that the debt to equity ratio is negative but is statistically insignificant in relation to MFIs' performance.

The deposit per loan ratio indicates self-sufficiency and an institution's ability to mobilize savings (Eur-U-Sa, 2011). Eur-U-Sa (2011) evaluated the performance of The BAAC in Thailand. The author finds that the deposit per loan ratio of the BAAC gradually increased between 1967 and 2009. This means that the bank is moving towards becoming a self-financing institution. Bhuiyan et al. (2011) evaluated the financial sustainability and outreach of MFIs in Malaysia and Bangladesh. They find that the deposit per loan ratio of MFIs in Malaysia is higher than the ratio in Bangladesh. This means that Malaysian MFIs have greater levels of self-financing than Bangladeshi MFIs. However, Bhuiyan et al. (2011) do not explain why the deposit per loan ratios of Malaysian MFIs are higher than Bangladeshi ratios.

The deposit per total asset ratio is measured by dividing total deposits by total assets. This ratio is only relevant for mobilizing MFIs' deposits. If an MFI has an efficient deposit programme, this ratio will be high. This means that an institution has low funding costs (Muriu, 2011). Muriu explains that external funding is more costly than deposits, thus MFIs may effectively use local depositors. However, Rahman and Mazlan (2014), who evaluated MFI sustainability in Bangladesh, find that Bangladeshi MFIs do not use deposits as their main source of funds. The main source of their funds comes from debt-financing, which explains why the debt to equity ratio of these MFIs is high. Evaluating Indian MFIs performance, Agarwal and Sinha (2010) find that most Indian MFIs do not use deposits as their primary funding source. The results, which are the same as Rahman and Mazlan's (2014) ones, show that the debt to equity ratio of these Indian MFIs is high. This means that their main funding is debt.

The gross loan portfolio per asset ratio is measured by dividing the gross loan portfolio by total assets. This ratio is one indicator that shows the financial structure. The ratio indicates the proportion of MFIs' core earning assets. Rahman and Mazlan (2014) use this ratio to compare the financial structure of five Bangladeshi MFIs. Their results show that the gross loan portfolio to assets ratio of Bangladeshi MFIs is high. Though Bhuiyan et al. (2011) use this variable to compare the

financial structure of Malaysian and Bangladeshi MFIs, their results reveal that Malaysian MFIs' ratio is higher than Bangladeshi MFIs' one.

MFI financial performance consists of ROA, ROE, and operational self-sufficiency. ROA is measured by dividing net operating income by total assets. This variable reflects an MFI's ability to deploy its asset profitably. Nyamsogoro (2010) shows that Tanzanian MFIs had a negative return on assets between 2001 and 2002 because these institutions were starting businesses in a new environment. Therefore, ROA experiences both positive and negative values. Rahman and Mazlan (2014) used this ratio to compare the financial performance of five Bangladeshi MFIs. They conclude that Bangladeshi MFIs are financially sustainable because this ratio is positive. Agarwal and Sinha (2010) used this variable to evaluate the financial performance of Indian MFIs. The authors find that MFIs in India are financially sustainable.

ROE is measured by dividing net operating income by total equity. ROE reflects the efficiency of operations and proper portfolio management in relation to equity (Nyamsogoro, 2010). This ratio is a crucial indicator for private investors when deciding whether to invest in MFIs (Ledgerwood, 1998). Shaoyan and Duwal (2012) used ROE to measure the operating performance of Nepalese MFIs. The authors state that ROE can be used to measure returns on owners' investments. Shaoyan and Duwal's (2012) result shows that Nepalese MFIs perform better than the global benchmark. Rahman and Mazlan (2014) used ROE to evaluate Bangladeshi MFIs sustainability. They find that ROE is positive, which means that Bangladeshi MFIs are financially sustainable.

Operational self-sufficiency is measured by dividing operating income by operating expenditure. Meyer (2002) states that operational self-sustainability means that the operating income is sufficient to cover operating costs (such as salaries and wages, supplies, loan losses, and other administrative costs). Some studies use this variable to evaluate MFI sustainability. Bogan (2012) evaluated how changes in capital structure can improve financial sustainability using operational self-sustainability. The author uses panel data from MFIs in Latin America, Asia, and Eastern Europe between 2003 and 2006. Bogan's results show that assets and capital structure affect MFIs' performance. Asset size is positive and significantly influenced by sustainability. The grant per asset ratio is significantly, negatively influenced by sustainability. The relationship between grant per asset and sustainability means that MFIs should rely less on grants, soft loans, and other types of donor funds. Sekabira (2013) investigated the sustainability of 14 MFIs in Uganda, based on capital structure. The study uses operational self-sustainability and financial self-sustainability to measure sustainability. Sekabira finds that debt and grants are negatively correlated with operational and financial self-sustainability and that capital structure is essential for MFIs' sustainability. The author states that when MFIs increase their debts, they struggle to make repayments. Moreover, when MFIs receive more grants,

operations become less competitive because these funds are given to borrowers at lower than market interest rates. This practice reduces interest revenue and funds for future operations.

3.3.2 Methodology

This study compares both VFs' and SGPs' performance, including MFI characteristics, outreach, productivity, financial structure and financial performance. The data were collected from the annual reports of MFIs between 2014 and 2016. VFs' and SGPs' annual reports were collected by the GSB between 2014 and 2016. GSB collected these data through the MFIs competition in Thailand. The MFIs competition is an annual contest run by the GSB. There are over 100 MFIs in Thailand that participate in this contest. This study uses data from 90 VFs and 70 SGPs in Thailand. The annual reports include the total number of members and borrowers, the total number of staff members, the total cash, loans outstanding, assets, liabilities, equity, revenue, expenses, and net profit. This study uses descriptive statistics to assess VFs' and SGPs' performance.

3.4 Determinants that Affect MFIs' Sustainability

In this section, we investigate the determinants that affect MFI sustainability. There are two sub-sections; the conceptual framework and the economic model and variables. The conceptual framework for MFIs' sustainability covers the definition, the concept, ideas and related research; the empirical model and the variables explain the econometric model.

3.4.1 Conceptual Framework

This section focuses on MFIs' sustainability in terms of financial sustainability. Kinde (2012) states that MFI financial sustainability is a key dimension of MFI sustainability. Financial sustainability is defined as an MFI's ability to cover all its costs from its own generated income without depending on subsidies or donations (Kinde, 2012). Dunford (2003) defines financial sustainability as the ability of an MFI to achieve its objectives without donor support. These definitions emphasize self-sufficiency (Kinde, 2012). Therefore, MFIs' sustainability means that an MFI can cover all its costs from its operational income.

Several studies have investigated the factors affecting MFIs' sustainability (Khan, Butt, & Khan, 2017; Kinde 2012; Rahman & Mazlan, 2014; Woldeyes, 2012). Woldeyes (2012) reviewed the factors that affect operational and financial sustainability of an MFI in Ethiopia, such as yield (yield on gross loan portfolio), portfolio at risk (PAR), the liquidity ratio (current ratio), the number of borrowers per staff member, cost per borrower, the operating expense ratio, the average disbursed loan size (depth of outreach), the size of the MFI, the debt to equity ratio, and the age. The author uses panel data regression, with six years of data (2005 to 2010) for 12 MFIs in Ethiopia. The author finds four factors

affect operational sustainability: the average loan balance per borrower; the size of the MFI; the cost per borrower; and the yield on gross loan portfolio. Woldeyes identifies three determinants that affect financial sustainability: cost per borrower, the number of active borrowers, and the yield on gross loan portfolio. The author finds that though MFIs in Ethiopia are operationally self-sufficient, they are not financially self-sufficient. The author recommends that these MFIs should reconsider the number of borrowers they have, serve borrowers at the lowest cost, and use their short-term assets to generate more cash and financial revenue. They should also increase loan size and the value of total assets.

Kinde (2012) examined the determinants that affect the financial sustainability of MFIs in Ethiopia. The author uses FSS to represent financial sustainability, with panel data regression for the period 2002 to 2010. The author identifies four factors that affect MFIs' sustainability: the breadth of outreach, the depth of outreach, the dependency ratio, and the cost per borrower. The author suggests that these MFIs should minimize their dependency on donated capital to be operationally competent. They should also increase the number of borrowers so that they can increase the volume of loans. However, an increase in loan volume does not guarantee financial sustainability. They should have an effective follow-up plan to ensure a higher repayment rate.

Rahman and Mazlan (2014) investigated the determinants that impact on the FSS of MFIs in Bangladesh. They use multiple regression and the independent variables from Woldeyes' (2012) study. The authors find only three factors affect FSS: MFI size, MFI age and the operating expense ratio. The authors recommend that MFIs in Bangladesh should reduce their dependence on donor funds, reduce operational costs, generate financial revenue and increase their total assets.

Khan et al. (2017) investigated the determinants that affect the FSS of MFIs in Pakistan, India, and Bangladesh. The authors use panel data from 2011 to 2015. They find that MFI size, the loan portfolio to total assets, portfolio at risk, the breadth of outreach, management inefficiency, and the operating cost ratio impact FSS. The authors suggest that these MFIs should increase their borrowers' repayment rates. They also suggest that MFI management should be more efficient in disbursing loans and collecting repayments and should reduce their transaction and administrative expenses.

For Thailand, Eur-U-Sa (2011) states that studies on MFI performance are still limited. Eur-U-Sa (2011) investigated BAAC performance and outreach. The author examined the relationship between outreach and financial performance, using data from BAAC's 2004 to 2009 annual reports. The author finds that the breadth of outreach indicators have complementary relationships with financial performance and financial sustainability. The results also show that the BAAC successfully manages its credit risk, which leads to good financial performance and financial sustainability. The BAAC has a

large outreach programme. However, the BAAC does not reach truly poor farmers because government policies, designed to reach them, are not effective. The author suggests that BAAC should design products that suit poor farmers, such as insurance products, more practice on joint liability group lending and cash-flow based lending.

This study focuses on FSS, which is defined as the ability of an MFI to achieve its objectives without donor support. The study follows the works of Dunford (2003) and Kinde (2012). I use determinants that affect the FSS of MFIs in Thailand based on panel data regression. I use secondary data as did Kinde (2012), Woldeyes (2012) and Khan et al. (2017).

3.4.2 Empirical Model and Variables

I use a panel regression model to identify the determinants of FSS of MFIs in Thailand. I use the panel regression model because of its advantages over cross-section and time-series data methods (Kinde, 2012). Kinde (2012) states that panel data involve the pooling of observations on a cross-section of units over several time periods. This can increase the degrees of freedom and, therefore, the power of the test (Kinde, 2012). It means that panel data are more useful than either cross-section or time-series data alone. Brook (2008) states that the advantages of using a panel data set include increasing the degrees of freedom and mitigating multicollinearity problems among the independent variables. The variables used in this model are derived from the Rahman and Mazlan's (2014) study. The panel regression model for FSS of MFIs (Kinde, 2012) is:

$$FSS_{it} = \alpha_i + \beta_1 YIE_{it} + \beta_2 LnSIZ_{it} + \beta_3 PP_{it} + \beta_4 DE_{it} + \beta_5 CB_{it} + \beta_6 LnALBPB_{it} + \beta_7 LnAG_{it} + \beta_8 LnMAB_{it} + \beta_9 OER_{it} + \epsilon_{it} \quad (3.31)$$

Where:

FSS: is the financial self-sufficiency ratio of MFI *i* at time *t*;

α_i : is a constant term;

YIE: is the yield on gross loan portfolio (+);

SIZ: is the total assets (+);

PP: is the personnel productivity ratio (+);

DE: is the debt to equity ratio (-);

CB: is the cost per borrower (-);

ALBPB: is the average loan balance per borrower (+);

AG: is the age of the MFI (+);

MAB: is the number of active borrowers (+);

OER: is the ratio of operating expense (-); and

ϵ : is the error term.

Table 3.3 defines the indicators used in the panel regression model.

Table 3.3 Financial Ratio Indicators for the MFI Sustainability Investigation

Variable	Calculation
<i>FSS</i>	$\frac{\text{Total Revenue}}{\text{Adjusted Expense}}$
<i>Yie</i>	$\frac{\text{Financial Revenue from Loan Portfolio}}{\text{Average Gross Loan Portfolio}}$
<i>Siz</i>	$\frac{\text{Total Assets}}{\text{Number of Active Borrowers}}$
<i>PP</i>	$\frac{\text{Number of Personnel}}{\text{Debt}}$
<i>DE</i>	$\frac{\text{Equity}}{\text{Operating Expenses}}$
<i>CB</i>	$\frac{\text{Average Number of Active Borrowers}}{\text{Gross Loan Portfolio}}$
<i>ALBPB</i>	$\frac{\text{Number of Active Borrowers}}{\text{Age of MFI}}$
<i>AG</i>	$\frac{\text{Number of Active Borrowers}}{\text{Operating Expense}}$
<i>MAB</i>	$\frac{\text{Number of Active Borrowers}}{\text{Average Gross Loan Portfolio}}$
<i>OER</i>	$\frac{\text{Operating Expense}}{\text{Average Gross Loan Portfolio}}$

Our hypotheses relating to the independent variables and FSS are based on findings in the literature. The yield on gross loan portfolio (+) is positively related to FSS. Woldeyes (2012) states that yield on gross loan portfolio shows an MFI's efficiency in generating cash revenue from its outstanding portfolio. Cull et al. (2007) assessed patterns of profitability, loan repayments and cost reductions in 124 micro-banks in 49 countries. The authors find that yield on gross loan portfolio is positive and significantly associated with FSS for individual lenders. However, the result is not true for village banks and solidarity group lenders. Cull et al. (2007) state that the yield on gross loan portfolio of both types of lender is negative and insignificant. Woldeyes (2012) concludes that yield on the gross loan portfolio indicates an MFI's ability to generate revenue that covers its financial and operating expenses. Similarly, Nyamsogoro (2010) evaluated the financial sustainability of MFIs in Tanzania and finds that there is a positive relationship between gross loan portfolio yield and FSS. Nyamsogoro's result provides evidence that an MFI's ability to generate revenue positively affects its financial sustainability.

MFI size is hypothesized to positively influence MFIs' FSS. Size can be measured using the value of an MFI's assets (Cull et al., 2007; Woldeyes, 2012). Cull et al. (2007) and Woldeyes (2012) find that the MFI size significantly positively affects the FSS of MFIs. Cull et al. (2007) conclude that MFIs size is significantly, positively related to three financial performance indicators: FSS, OSS, and ROA. Woldeyes (2012) agrees with Cull et al.'s (2007) argument that an increase in size causes a positive change in OSS. Mersland and Storm (2009) state that size is associated with the FSS of MFIs and conclude that larger MFIs have more capital thus they can reach more people than smaller MFIs.

The personnel productivity ratio is hypothesized to positively influence the FSS of MFIs. This is measured by dividing the number of active borrowers by the number of loan officers (CGAP, 2003). However, loan officers have some duties that overlap with other microfinance staff. Thus, productivity can be measured by dividing active borrowers by the number of officers (Kinde, 2012). This ratio is the personnel productivity ratio. A higher ratio reflects an MFI's ability to use its staff efficiently. Nyamsogoro (2010) studied the relationship between the number of borrowers per staff member and the financial sustainability of rural Tanzanian MFIs. The author's results show a negative, strong statistically significant relationship between borrowers per staff member and financial sustainability. However, Nyamsogoro also concludes that Tanzanian MFIs' staff in rural areas are not efficient because they fail to manage borrowers when the number of borrowers grows.

The debt to equity ratio is hypothesized to negatively influence the FSS of MFIs. This ratio indicates the capital structure. A high ratio implies that MFIs are leveraged rather than financed through equity capital (Kinde, 2012). Kinde (2012) investigated the factors affecting the FSS of Ethiopian MFIs. The author finds that debt to equity has a negative, statistically insignificant impact on FSS. This result implies that the combination of various sources of capital does not improve an MFI's FSS. The negative coefficient shows that the more MFIs are debt-financed than by other sources of finance, the less sustainable they are. According to Nyamsogoro (2010), equity is a relatively cheap source of funding; equity can improve MFIs' sustainability. The author shows that capital structure is positively correlated with MFIs' sustainability. The capital structure represents the percentage of equity to total long-term capital. Therefore, a positive coefficient shows that the more MFIs are equity financed (than with other sources of finance), the greater the improvement in their sustainability. This result could be caused by the fact that owners benefit not from debt, but rather from the loans given to them. This makes equity a cheaper source of finance. In short, it improves financial sustainability.

Cost per borrower covers MFI efficiency. This variable evaluates the cost of MFI management. Some studies have investigated the relationship between cost per borrower and MFI sustainability. Kinde (2012) evaluated the financial sustainability of Ethiopian MFIs and finds that there is a negative relationship between the cost per borrower and financial sustainability. The result indicates that an

increase in cost per borrower reduces MFIs' financial sustainability. This result implies that cost reductions can improve financial sustainability. Woldeyes (2012) reviewed the factors that affect Ethiopian MFI sustainability and finds that there is a negative, statistically significant correlation between the cost per borrower and MFIs' sustainability. The result indicates that an increase in cost per borrower reduces MFIs' operational sustainability.

The average loan balance per borrower is measured using the depth of outreach (Ledgerwood, 1998). This means that smaller loans reflect poorer clients (Cull et al., 2007; Mersland & Storm, 2009). Cull et al. (2007) studied the financial performance and outreach of 124 MFIs in 49 developing countries. The authors state that average loan size is a proxy for a customer's poverty level. This variable indicates that smaller loans show poorer customers. Some studies examined the relationship between average loan balance per borrower and MFI sustainability. Adongo and Stork (2005) investigated the factors that influence the financial sustainability of Namibian MFIs. They find that profitability is related to bigger loans. Similarly, Nyamsogoro (2010) evaluated the financial sustainability of Tanzanian MFIs and finds that there is a positive, statistically significant correlation between the average loan balance per borrower and MFIs' sustainability. The result indicates that MFI profitability is associated with larger loan size. That means larger loans are related to greater cost efficiency and, therefore, profitability.

MFI age may impact MFIs' sustainability. This variable refers to the period that an MFI has been in operation (Woldeyes, 2012). Kar (2012) states that older MFIs may benefit from organizational learning. The learning pattern involves a first period of speeding up and then slowing down, because the practically feasible level of development is reached. Therefore, MFIs' age is hypothesized to initially affect MFI sustainability positively and then negatively. Cull et al (2007) evaluated the financial performance and outreach of 124 MFIs in 49 developing countries. The authors find a positive relationship between MFI age and sustainability. In contrast, Nyamsogoro (2010) finds that in Tanzania MFI age is not related to financial sustainability.

The number of active borrowers is hypothesized to positively affect MFI sustainability. In their study of Indian MFIs, Crombrugghe, Tenikue and Sureda (2008) state that increasing the number of borrowers per officer raises the OSS and FSS. This result indicates a positive relationship between the number of borrowers and profitability. This means that the cost of serving one more borrower in microfinance programmes increases minimally. Therefore, increasing the number of borrowers raises an MFI's sustainability. Likewise, Kinde (2012) finds that there is a positive relationship between active borrowers and MFI sustainability. This is because increasing the number of borrowers increases the number of sales, which is one way to maximize profitability and ultimately financial sustainability. The author also states that when the number of borrowers increases, MFIs enjoy an

economy of scale and so reduce their costs, leading to financial sustainability. In contrast, Nyamsogoro (2010) finds that active borrowers are negatively related to financial sustainability in Tanzania. Nyamsogoro explains that Tanzanian microfinance staff are not efficient, therefore they cannot manage when the number of borrowers increases.

Operating expense ratio is hypothesized to negatively affect MIFs' sustainability. Nyamsogoro (2010) finds that the operating expense ratio is negatively related to Tanzanian MFIs' sustainability. This means that if MFIs can reduce operating costs, they will be more efficient leading to financial sustainability. Dissanayake (2012) investigated factors affecting MFI profitability in Sri Lanka. The author finds that the operating expense ratio has a negative, statistically significant correlation with MFI sustainability. The author concludes that this variable is a statistically significant predictor variable in evaluating the OSS of Sri Lankan MFIs. Dissanayake states that this variable provides an overall measure of MFI efficiency. Efficiency in management practices enables MFIs to reach more clients and attain higher profit.

Following the panel regression model above, the estimated impact of the independent variables on MFIs' FSS is assessed in terms of the statistical significance of the coefficient β_i . However, some variables are omitted from the model. Therefore, without controlling for these variables, the estimated coefficients result in omitted variables bias (Woodridge, 2009). Two methods are commonly used to deal with omitted variables: the Fixed Effect (FE) method and the Random Effect (RE) method (Hsiao, 2007). Hausman's test is used to select the more appropriate method. This test is based on differences between FE and RE results (Verbeek, 2008; Woldeyes, 2012). The key consideration in choosing between FE and RE is the correlation between X_{it} and ϵ_{it} . FE is assumed to be consistent when X_{it} and ϵ_{it} are correlated. In contrast, RE is assumed to be consistent when X_{it} and ϵ_{it} are not correlated (Verbeek, 2008; Woldeyes, 2012). Verbeek (2008) states that FE estimators are consistent when X_{it} and ϵ_{it} are correlated, whereas the RE estimator is consistent and efficient only if X_{it} and ϵ_{it} are not correlated.

The data used in this section were obtained from VFs' and SGPs' annual reports. These data were collected by the GSB between 2014 and 2016. The GSB collected the data through the microfinance competition in Thailand. There are 90 VFs and 70 SGPs in Thailand with complete annual reports. The annual reports include the number of members, borrowers and staff, the cash, loans outstanding, assets, liabilities, equity, revenue, expenses and net profit.

In summary, this section has outlined the panel regression model that will be used to investigate the factors affecting MFI sustainability. The panel regression model was chosen because it increases the degrees of freedom and resolves multicollinearity problems among the explanatory variables (Kinde, 2012).

3.5 Chapter Summary

This study uses four methods to answer the research questions. First, the multinomial logit model is used to determine household characteristics that affect their participation in microfinance programmes. Secondly, the PSM and the fixed effect models are used to examine the impact of microfinance programmes on individual's and households' economic and social welfare. These methods solve selection bias problems (Carreras, 2012). Thirdly, the study examines MFI performance using the institutional characteristics of outreach, productivity, financial structure and financial performance. Finally, the study uses the panel regression technique, which involves the pooling of observation units in cross-sectional data over several time periods, to investigate the determinants that affect MFIs' sustainability. This method can be used to address a broader range of issues and tackle more complex problems (Kinde, 2012). Panel data combine cross-sectional data and time series data. This can increase the degrees of freedom and, therefore, the power of the test (Kinde, 2012). The model can also solve multicollinearity problems among the explanatory variables that can arise if the time series model is used alone (Kinde, 2012). The next chapter presents and discusses the results of the empirical models to determine which household characteristics affect participation in microfinance programmes. It also examines the impact of microfinance programmes on individual's and households' economic and social welfare.

Chapter 4

Empirical Results

This chapter discusses the empirical results of the credit participation and welfare impact models. The chapter is organized as follows: Section 4.1 describes borrower and non-borrower characteristics for microfinance programmes. Section 4.2 discusses the factors that influence household participation in microfinance programmes. Section 4.3 discusses the impact of MFI participation on individual household's economic and social welfare. Finally, Section 4.4 summarizes the findings.

4.1 The Characteristics of Microfinance Borrowers and Non-borrowers

This section discusses the socio-economic and demographic characteristics of borrowers and non-borrowers. As noted in the previous chapter, it uses cross-sectional data from the Socioeconomic Survey (2017) which was collected by the National Statistical Office of the Ministry of Information and Communication Technology. Briefly, the survey interviewed 43,210 households (both borrowers and non-borrowers) across the country. Of the 43,210 samples, 8,216 (19.01%) households borrowed from VFs, 5,394 (12.48%) households borrowed from SGPs and 799 (1.85%) households borrowed from both VFs and SGPs. Two thirds (28,801, 66.65%) of the sampled households were non-VF and SGP borrowers.

Table 4.1 summarizes the borrowers' and non-borrowers' characteristics. One-way ANOVA (F-test) was used to assess whether the mean values of VFs, SGPs, both VFs and SGPs, and non-VF and SGP borrowers were statistically different. The Chi-square test was used to evaluate the relationship between non-metric household variables and credit participation. The one-way ANOVA (F-test) shows that all variables are statistically significant at the 99% level; in short, the mean value of age, education, household size, dependency ratio, number of children, number of elderly, monthly income, monthly expenditure on food and beverages, financial assets, number of cars and number of motorcycles in at least one group are different from the rest. The Chi-square tests are also statistically significant at the 99% level. This suggests that microfinance participation is strongly associated with marital status, occupation and the household's geographical location.

In terms of household head characteristics, the average age of the sample is 54.64 years. VF borrowers are the oldest, with an average age of 56.90 years; SGP borrowers are the youngest, with an average age of 49.12 years. The average ages of the VF and SGP borrowers and non-VF and SGP borrowers are 54.16 and 55.05 years, respectively (see Table 4.1). In terms of gender, approximately 40% of all the members of the four groups are female. SGP borrowers have the highest education level (9.31 years) and VF borrowers have the lowest education level (6.36 years).

Table 4.1 The Characteristics of Thai Borrowers and Non-borrowers from MFIs

Variable	Non-VF and SGP Borrowers	VF Borrowers	SGP Borrowers	Both VF and SGP Borrowers	All Respondents	Statistical Test
Household Head Characteristic						
Age (years)	55.05	56.90	49.12	54.16	54.64	F= 314.07***
Female (yes=1)	0.41	0.37	0.36	0.41	0.40	chi2= 57.3820***
Education (years)	8.39	6.36	9.31	6.73	8.08	F= 735.05***
Married (yes=1)	0.58	0.75	0.73	0.76	0.64	chi2 = 1.0e+03***
Single (yes=1)	0.14	0.02	0.10	0.02	0.11	chi2 = 917.7399***
Demographic						
Household Size (persons)	2.60	3.31	3.40	3.83	2.86	F= 869.16***
Dependency Ratio	0.42	0.35	0.33	0.35	0.39	F= 161.15***
Number of Children (age < 15 yrs) (persons)	0.41	0.69	0.67	0.90	0.50	F= 436.72***
Number of Elderly (age > 60 yrs) (persons)	0.65	0.67	0.40	0.51	0.62	F= 178.55***
Occupation						
Farmer (yes=1)	0.26	0.71	0.24	0.54	0.35	chi2 = 6.2e+03***
Entrepreneur (yes=1)	0.03	0.02	0.06	0.04	0.03	chi2 = 124.3592***
Formal Worker (yes=1)	0.32	0.19	0.44	0.31	0.31	chi2 = 1.0e+03***
Informal Worker (yes=1)	0.33	0.61	0.33	0.51	0.38	chi2 = 2.3e+03***
Income, Expenditure and Assets						
Monthly Income (THB 1,000)	25.90	17.77	37.67	25.17	25.81	F= 222.83***
Monthly Expenditure on Food and Beverages (THB 1,000)	7.02	6.29	9.10	7.72	7.16	F= 449.43***
Financial Assets (THB 1,000)	196.40	67.08	167.52	70.80	165.88	F= 89.86***
Number of Cars	0.22	0.07	0.38	0.16	0.21	F= 452.47***
Number of Motorcycles	1.07	1.47	1.50	1.69	1.21	F= 764.15***
Other Variables						
Central (yes=1)	0.30	0.18	0.35	0.32	0.29	chi2 = 621.5546***

Variable	Non-VF and SGP Borrowers	VF Borrowers	SGP Borrowers	Both VF and SGP Borrowers	All Respondents	Statistical Test
North (yes=1)	0.23	0.31	0.19	0.27	0.24	chi2 = 377.6739***
Northeast (yes=1)	0.22	0.47	0.19	0.35	0.26	chi2 = 2.2e+03***
South (yes=1)	0.18	0.04	0.22	0.06	0.16	chi2 = 1.2e+03***
Rural Household (yes=1)	0.36	0.54	0.35	0.49	0.39	chi2 = 987.3302***
Difficulty Obtaining an Emergency Loan (yes=1)	0.08	0.03	0.05	0.04	0.07	chi2 = 324.9032***
Total	28,801	8,216	5,394	799	43,210	

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

In terms of marital status, 58% of non-VF and SGP borrowers, 75% of the VF borrowers, 73% of the SGP borrowers and 76% of both VF and SGP borrowers are married. There is an average of three people per household in all four groups (VF and SGP borrowers, both VF and SGP borrowers, and non-VF and SGP borrowers). The dependency ratio is defined as the ratio of non-workers to workers in each household (Fongthong & Suriya, 2014). Non-VF and SGP borrowers have the highest dependency ratio (0.42). SGP borrowers have the lowest dependency ratio (0.33). The data show that the number of children and elderly in all four groups is less than one person per household (see Table 4.1).

Though most non-VF and SGP borrowers are informal workers (self-employed, contributing family workers), most VF borrowers are farm workers. SGP borrowers are formal workers (government employees, state enterprise employees and private company employees). In terms of occupation, most borrowers in the third group (who borrow from both VFs and SGPs) are farmers. SGP borrowers have the highest monthly income and monthly expenditure on food and beverages (THB 37.67 and THB 9.10 thousand per household, respectively). VF borrowers have the lowest monthly income and expenditure on food and beverages of the three groups (THB 17.77 and THB 6.29 thousand per household, respectively). Both VF and SGP borrowers and non-VF and SGP borrowers have monthly household incomes between THB 25.17 and THB 25.90 thousand and monthly expenditure on food and beverages of between THB 7.02 and THB 7.72 thousand, respectively (see Table 4.1).

Households from the four groups possess many financial assets (see Table 4.1). The average value of financial assets is THB 165.88 thousand per household. Non-VF and SGP borrowers have the most financial assets and VF borrowers have the least. SGPs borrowers have the highest average number of cars (0.38 cars) and VF borrowers have the lowest average number of cars (0.07 cars). Both VF and SGP borrowers have the highest average number of motorcycles (1.69 motorcycles), whereas non-VF and SGP borrowers, VF borrowers and SGP borrowers have 1.07, 1.47 and 1.50 motorcycles, respectively.

Most VF borrowers (54%) live in rural areas. Thirty-six percent of non-VF and SGP borrowers and 35% of SGP borrowers live in rural areas. A minority of non-VF and SGP borrowers, VF, SGP, and both VF and SGP borrowers have had trouble accessing loans when faced with an emergency: 8%, 3%, 5% and 4%, respectively (see Table 4.1).

4.2 Factors Influencing Microfinance Participation

There is a variety of factors that influence participation in microfinance programmes. This study includes four alternatives (borrowing from either a VF, or an SGP, or borrowing from both a VF and an SGP, or non-VF and SGP borrowing) in the multinomial logit model to investigate household

borrowing choices. Non-VF and SGP borrowing is taken as a base outcome so that the VF, SGP and both VF and SGP coefficients indicate (significant) differences from non-VF and SGP borrowing.

4.2.1 Model Specification

The multinomial logit model is coded as four outcomes that affect microfinance credit participation (1 = non-VF and SGP borrowing; 2 = borrowing from VFs (only); 3 = borrowing from SGPs (only); 4 = borrowing from both VFs and SGPs). The model is interpreted in terms of the odds ratios. The odds ratio is defined as the probability of outcome i versus outcome u (Balogun & Yusuf, 2011; Durojaiye et al., 2014; Mpuga, 2008; Verbeek, 2008) (see section 3.1.2) is:

$$\frac{P_n(T_n=i)}{P_n(T_n=u)} = \exp[X_n(\beta_i - \beta_u)] \quad (4.1)$$

Where

$P_n(T_n = i)$: Probability of observing outcome i

$P_n(T_n = u)$: Probability of observing outcome u

X : A vector of characteristics, including household head characteristics and demographics, household size, occupations, income and assets

β : Parameters to be estimated

For the purpose of interpretation, equation (4.1) is transformed into a log form. Equation (4.2) expresses the multinomial logit model, which is linear in the logit (Balogun & Yusuf, 2011; Durojaiye et al., 2014; Mpuga, 2008; Verbeek, 2008):

$$\ln \frac{P_n(T_n=i)}{P_n(T_n=u)} = [X_n(\beta_i - \beta_u)] \quad (4.2)$$

The difference between β_i and β_u in equation (4.2) is the influence of X on the logit of outcome i versus outcome u . Equation (4.2) can compute the partial derivative easily because the model is linear in logit.

$$\frac{\partial \ln \frac{P_n(T_n=i)}{P_n(T_n=u)}}{\partial X_n} = \frac{\partial X_n(\beta_i - \beta_u)}{\partial X_n} = (\beta_i - \beta_u) \quad (4.3)$$

4.2.2 Estimation Strategies

The multinomial logit model has several estimation tests that are commonly used in association with the model (Freese & Long, 2000). The first consideration is to test all coefficients associated with an independent variable that are simultaneously equal to zero. This study uses the Likelihood Ratio test

(LR test). The LR results test whether an independent variable affects a dependent variable (Freese & Long, 2000; Long & Freese, 2014). The second consideration is to test for combining dependent categories. The Wald test is used to test if any of the independent variables significantly affects the odds of outcome i versus outcome u . This indicates that i and u are indistinguishable with respect to the variables in the model. This test is commonly used to determine if two outcomes can be combined (Freese & Long, 2000; Long & Freese, 2014; Williams, 2018). The last step is to assess the Independence of Irrelevant Alternatives (IIA) assumption. The Hausman test is used to test whether the model violates the IIA assumption (Freese & Long, 2000; Hausman & McFadden, 1984; Long & Freese, 2014). The IIA assumption implies that adding another alternative or changing the characteristics of a third alternative does not affect the relative odds between alternatives i and u (Wooldridge, 2007).

This study conducts an LR test for each independent variable. Table 4.2 shows the test results for the independent variables. The results show that all variable effects are significant at the 0.01 level. This finding indicates that independent variables affect the dependent variable.

Table 4.3 shows the Wald test results for combining outcome categories. The results show that all combinations are significant at the 0.01 level. This indicates that no categories should be combined.

Table 4.2 The Likelihood Ratio Test of the Independent Variables

Independent Variable	chi2	df	P>chi2
Household Head Characteristic			
Age (years)	221.825	3	0.000
Female (yes=1)	116.598	3	0.000
Education (year)	103.85	3	0.000
Married (yes=1)	72.201	3	0.000
Single (yes=1)	115.087	3	0.000
Demographic			
Household Size (persons)	587.989	3	0.000
Dependency Ratio	221.427	3	0.000
Number of Children (age < 15 yrs) (persons)	13.704	3	0.003
Number of Elderly People (age > 60 yrs) (persons)	108.274	3	0.000
Occupation			
Farmer (yes=1)	889.8	3	0.000
Entrepreneur (yes=1)	46.653	3	0.000
Formal Worker (yes=1)	76.222	3	0.000
Informal Worker (yes=1)	88.126	3	0.000
Income and Assets			
Monthly Income (THB 1,000)	64.179	3	0.000
Monthly Expenditure on Food and Beverages (THB 1,000)	53.679	3	0.000
Financial Assets (THB 1,000)	216.192	3	0.000
Number of Cars	204.36	3	0.000
Number of Motorcycles	158.319	3	0.000

Independent Variable	chi2	df	P>chi2
Other Variables			
Central (yes=1)	213.309	3	0.000
North (yes=1)	320.869	3	0.000
Northeast (yes=1)	383.008	3	0.000
South (yes=1)	35.905	3	0.000
Rural Households (yes=1)	117.145	3	0.000
Difficulty Obtaining an Emergency Loan (yes=1)	121.616	3	0.000

Source: Author's calculations

Table 4.3 The Wald Test of Combining Outcome Categories

Independent Variable	chi2	df	P>chi2
Non-VF and SGP & VF	6048.291	24	0.000
Non-VF and SGP & SGP	2551.648	24	0.000
Non-VF and SGP & Both VF and SGP	947.118	24	0.000
VF & SGP	4601.939	24	0.000
VF & Both VF and SGP	407.126	24	0.000
SGP & Both VF and SGP	562.636	24	0.000

Source: Author's calculations

The Hausman test evaluates whether the IIA assumption holds for the multinomial logit model. The Hausman test results for IIA (see Table 4.4) reveal that the null hypothesis of IIA cannot be rejected. This indicates that IIA is not violated.

Table 4.4 The Results of the Hausman Test of Independence of Irrelevant Alternatives

Omitted Category	Hausman Test		
	Test Statistic	P-value	Evidence
Non-VF and SGP Borrower	60.337	0.129	For IIA
VF Borrower	-31.301	-	For IIA
SGP Borrower	-187.635	-	For IIA
Both VF and SGP Borrower	-53.004	-	For IIA

Source: Author's calculations

4.2.3 Results and Discussion

This section discusses the multinomial logit estimation results, a test conducted to investigate the determinants affecting household participation in microfinance programmes. The model is estimated using the MLE technique. Table 4.5 presents the estimated results of the multinomial logit model specified in equation (4.2).

Table 4.5 presents the microfinance programme participation determinants and includes parameter estimates and marginal effects. Overall, 41,099 observations were used to calculate the estimated coefficients. The LR test ($\chi^2_{42} = 13911.19$) rejects the null hypothesis that the parameter estimates for the multinomial logit model are zero; the model can be used to explain the probability of

microfinance programme participation. The multinomial logit model estimates the coefficients via MLE. However, the value of the estimated coefficients from the multinomial logistic regression have no direct economic interpretation because they are obtained using MLE techniques (Greene, 2003; Li, 2010). To address this limitation, this study calculates the marginal effect provided in Table 4.5. Marginal effects provide greater intuition in terms of interpreting the estimated coefficients of continuous explanatory variables, whereas the odds ratios are more useful for interpreting the estimated coefficients of the dichotomous explanatory variables (Greene, 2003; Li, 2010).

4.2.4 The Determinants of VF Participation

Column 1, Table 4.5, shows that VF participation is significantly explained by: household head characteristics (age, female, education, married, single), demographics (household size, dependency ratio, number of children, number of elderly people), occupation (farmer, entrepreneur, formal and informal worker), income, expenditure, and assets (monthly income, monthly expenditure on food and beverages, financial assets, number of cars, number of motorcycles), and other variables (central, north, northeast, south, rural households, difficulty obtaining an emergency loan).

Table 4.5 Multinomial Logit Model Results for Predicting Borrower Choices of Microfinance Programmes in Thailand

	VF Borrowers			SGP Borrowers			Both VF and SGP Borrowers		
	Coefficient	S.E.	Marginal Effect	Coefficient	S.E.	Marginal Effect	Coefficient	S.E.	Marginal Effect
Constant	-6.115***	0.440		-1.560***	0.159		-8.197***	1.079	
Household Head Characteristic									
Age (years)	0.009***	0.002	$1.131 \times 10^{-03***}$	-0.0239***	0.002	$-2.539 \times 10^{-03***}$	-0.001	0.005	5.30×10^{-06}
Female (yes=1)	0.349***	0.035	0.032***	0.065*	0.037	1.68×10^{-03}	0.473***	0.087	$4.547 \times 10^{-03***}$
Education (year)	-0.044***	0.006	$-4.273 \times 10^{-03***}$	0.018***	0.005	$2.428 \times 10^{-03***}$	-0.073***	0.015	$-7.082 \times 10^{-04***}$
Married (yes=1)	0.358***	0.043	0.032***	0.030	0.049	-1.424×10^{-03}	0.30***	0.113	$2.536 \times 10^{-03**}$
Single (yes=1)	-0.739***	0.088	-0.052***	-0.386***	0.071	-0.028***	-1.292***	0.313	$-8.032 \times 10^{-03***}$
Demographic									
Household Size (persons)	0.265***	0.019	0.020***	0.397***	0.019	0.037***	0.413***	0.042	$3.428 \times 10^{-03***}$
Dependency Ratio	-0.214***	0.074	-5.452×10^{-03}	-1.153***	0.080	-0.114***	-0.652***	0.203	$-5.00 \times 10^{-03**}$
Number of Children (age < 15 yrs) (persons)	0.049*	0.029	$5.411 \times 10^{-03**}$	-0.076**	0.030	$-8.453 \times 10^{-03***}$	0.099	0.066	1.041×10^{-03}
Number of Elderly People (age > 60 yrs) (persons)	-0.195***	0.027	-0.015***	-0.233***	0.031	-0.021***	-0.358***	0.069	$-3.140 \times 10^{-03***}$
Occupation									
Farmer (yes=1)	1.050***	0.039	0.116***	-0.240***	0.045	-0.038***	0.458***	0.096	$3.709 \times 10^{-03***}$
Entrepreneur (yes=1)	0.641***	0.108	0.070***	0.159*	0.091	4.228×10^{-03}	1.060***	0.238	0.015***
Formal Worker (yes=1)	0.452***	0.065	0.046***	-0.124**	0.063	-0.019***	0.744***	0.159	$8.246 \times 10^{-03***}$
Informal Worker (yes=1)	0.414***	0.058	0.043***	-0.256***	0.062	-0.031***	0.493***	0.150	$5.097 \times 10^{-03***}$
Income, Expenditure, and Assets									
Monthly Income (THB 1,000)	-0.007***	0.001	$-6.941 \times 10^{-04***}$	0.001***	3.415×10^{-04}	$2.258 \times 10^{-04***}$	0.001	0.001	$1.77 \times 10^{-05*}$
Monthly Expenditure on Food and Beverages (THB 1,000)	-0.044***	0.006	-0.004***	-0.003	0.004	2.439×10^{-04}	-0.028**	0.012	$-2.348 \times 10^{-04*}$
Financial Assets (THB 1,000)	-0.001***	1.102×10^{-04}	$-8.18 \times 10^{-05***}$	$-3.603 \times 10^{-04***}$	4.49×10^{-05}	$-2.32 \times 10^{-05***}$	$-1.849 \times 10^{-03***}$	3.374×10^{-04}	$-1.72 \times 10^{-05***}$

	VF Borrowers			SGP Borrowers			Both VF and SGP Borrowers		
	Coefficient	S.E.	Marginal Effect	Coefficient	S.E.	Marginal Effect	Coefficient	S.E.	Marginal Effect
Number of Cars	-0.343***	0.050	-0.037***	0.360***	0.032	0.041***	0.068	0.010	6.335×10^{-04}
Number of Motorcycles	0.142***	0.021	0.010***	0.222***	0.020	0.021***	0.284***	0.047	$2.456 \times 10^{-03***}$
Other Variables									
Central (yes=1)	3.0***	0.411	0.416***	0.307***	0.073	-0.039***	3.358***	1.00	0.054
North (yes=1)	3.533***	0.412	0.552***	0.222***	0.080	-0.066***	3.496***	1.007	0.052
Northeast (yes=1)	3.722***	0.411	0.561***	0.206***	0.078	-0.067***	3.517***	1.006	0.046
South (yes=1)	1.596***	0.415	0.213***	0.197**	0.078	-0.015	1.807*	1.015	0.027
Rural Households (yes=1)	0.322***	0.030	0.031***	0.015	0.035	-2.722×10^{-03}	0.209***	0.077	$1.768 \times 10^{-03**}$
Difficulty Obtaining an Emergency Loan (yes=1)	-0.749***	0.077	-0.052***	-0.293***	0.068	-0.021***	-0.610***	0.197	$-4.236 \times 10^{-03**}$
Number of Observations	41,099								
Log Likelihood	-31240.817								
LR chi2(42)	13911.19								
Prob > chi2	0.0000								
Pseudo R2	0.1821								

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

In terms of household head characteristics, being female and/or married are significant positive predictors of VF participation at the 1% level. Age is significant and positive at the 1% level, but higher levels of education and being single are negative and significant at the 1% level. This indicates that female household heads borrow more from VFs than male household heads. The marginal effect of the female coefficient shows that the probability of being a VF borrower increases by 3.20% when the borrower is female (see Column 1, Table 4.5). This result does not support previous evidence in Zeller (1994), Evans et al. (1999) and Li (2010) who all argue that women's limited mobility and freedom from family domination lead to decreasing demand for credit, thus decreasing the likelihood of microfinance participation. However, this result supports Fongthong and Suriya's (2014) study that investigated the determinants affecting household access to VFs in Thailand. They find that committees actively encourage women to borrow because they are a much lower credit risk. Cull et al. (2016, 2018) explains that many microfinance programmes, especially subsidized credit programmes, favour women because they are a lower credit risk; therefore, they are more likely to access microfinance programmes. In short, VFs not only encourage women to access loans but also to participate as committee members.

In terms of age, the results show that older household heads are more likely to borrow from VFs. Holding all other determinants constant, the marginal effect of age indicates that an increase of a year in household-head age increases the probability of borrowing by 0.11% (Column 1, Table 4.5). Our result is similar to that of Zeller (1994), who finds that age is likely to increase the probability of formal microcredit participation in rural Madagascar. Eularie and Vishwanatha (2016), who evaluated the factors affecting small farmers' access to microcredit in Rwanda, find that young small-scale farmers are not involved in microcredit activities, but older small-scale farmers are more interested. They explain that older household heads are more aware of the importance of microcredit programme participation for poverty reduction and improved livelihood than younger household heads.

The married coefficient is positive and significant at the 1% level and the single coefficient is negative and significant at the same level. The marginal effect of the married and single coefficients indicates that the probability of becoming a VF borrower increases by 3.20% when the borrower is married and decreases by 5.20% when the borrower is single (Column 1, Table 4.5). These findings support some prior studies. Mpuga (2008), who investigated accessibility and demand for credit in rural Uganda, shows that people who are married are more likely to be stable thus, lenders are more likely to view them as reliable. Therefore, they are more likely to access credit than their single counterparts. Phan's (2012) investigation of factors affecting rural households' access to microcredit in Vietnam finds a positive sign for the married variable at the 5% level, which indicates that such individuals are more likely to participate in these programmes. Wachira and Kihui (2012), who

evaluated the impact of financial literacy on access to financial services in Kenya, explain that informal service providers are more likely to grant loans to married persons because they are seen as being more trustworthy as they move from one life stage to another.

The results show that well-educated household heads are less likely to borrow from VFs. Holding all other determinants constant, the marginal effect of education indicates that an increase in the number of years of a household head's education decreases the probability of borrowing by 0.43% (Column 1, Table 4.5). This contradicts some previous studies. Mpuga (2008), Tang et al. (2010) and Li et al. (2011a) argue that a borrowers' education level is positively related to participation in microfinance programmes. Higher levels of education are associated with higher levels of human capital, which, in turn, leads to higher rates of microfinance participation. However, this study's finding could suggest that microfinance programmes usually target borrowers with lower levels of education. Fongthong and Suriya (2014) evaluated whether the VF reached the poor in Thailand. They find that VF borrowers have lower education levels. Similarly, Kasali et al. (2016), who examined the determinants that affect poor households' access to microfinance programmes in Nigeria, find that microfinance borrowers tend to have lower education levels.

For the demographic characteristics (household size, dependency ratio, number of children, number of elderly people), the results show a significant positive relationship between household size and microfinance participation. This implies that larger households are more likely to participate in VFs by 2% (Column 1, Table 4.5). Fongthong and Suriya (2014) state that the larger a household is, the greater the likelihood that they will borrow from VFs. These households have more income sources and, as a result, are more capable of repaying their loans. Saqib et al. (2016), who explored the factors affecting farmers' access to agricultural credit, find that household size has a positive coefficient, significant at the 0.01 level. The authors explain that, as the household size increases, farmers are more likely to use agricultural loans as a risk management strategy. Nguyen (2007), who examined the determinants of credit participation of Vietnamese households, finds that household size has a significant effect on credit participation. The author explains that labour demand increases during peak times (such as harvests) and this could be one reason why household size affects the probability of gaining a loan. Sarap (1990), who investigated factors that affect small farmers' access to credit in India, reveals that larger household size increases credit demand as household resources are diverted into agricultural activities. Without hiring staff, small households have less capacity to expand their business, which leads to a lower level of microfinance participation. This study's results suggest that larger households have more income sources and, as a result, are more capable of repaying their loans. In short, these households borrow to expand their businesses.

The dependence ratio coefficient is negative and significant at the 1% level. This result implies that individuals who are less economically active have a lower probability of borrowing from VFs. This finding suggests that households with high dependency ratios have fewer family members to help generate income and, therefore, are less able to repay their loans. These households must allocate money to look after their children and elderly members, which potentially affects their ability to repay loans (Fongthong & Suriya, 2014). Moreover, the number of elderly coefficient is negative and significant at the 1% level. This finding indicates that if a household has elderly members, the household is less likely to participate in VFs by 1.50% compared to other households, all other factors held constant (Column 1, Table 4.5). Our result suggests that households that have more elderly members are less able to repay loans. In short, financial services providers consider the elderly less creditworthy (Wachira & Kihiu, 2012).

The positive number of children coefficient at the 10% level indicates that if households have more children, they are more likely to participate in VFs by 0.54% compared to other households, all other factors being constant (Column 1, Table 4.5). Our finding supports Phan's (2012) study, which finds that households with a greater number of children tend to have higher levels of microcredit programme participation. The author explains that households with more children have greater levels of financial stress and that the proportion of households with over three children in the borrower group is significantly greater at the 1% level than households with fewer than three children in the non-borrower group. Therefore, the non-borrower group is less likely to be financially stressed than the borrower group. Likewise, Menkhoff and Rungruxsirivorn (2011), who compared borrowers' characteristics between VFs and six other financial institutions in three provinces of northeast Thailand, find that households with more children have a higher probability of applying for loans.

At the 1% significance level, farmers, entrepreneurs, formal workers and informal workers are more likely to participate in VFs by 11.60%, 7%, 4.60% and 4.30%, respectively, than other households based on occupation (Column 1, Table 4.5). These results suggest that farmers, entrepreneurs, formal workers and informal workers are the VF's primary borrowers. VFs were developed to provide finance for occupational development, job creation, income generation activities and welfare improvement (Fongthong & Suriya, 2014). Farmers, entrepreneurs, formal workers and informal workers typically use loans to generate income. Lewis et al. (2013) explain that the VF provides good loan coverage, reaching the lowest income groups, including unskilled occupational groups.

Income, expenditure and assets, monthly income, monthly expenditure on food and beverages, financial assets, the number of cars, and the number of motorcycles, are significant in explaining VF participation. The results show that monthly income and monthly expenditure on food and

beverages are negative and significant at the 1% level. The marginal effect of monthly income and monthly expenditure on food and beverages show that for every THB 1,000 increase in monthly income and monthly expenditure on food and beverages will decrease the probability of VF participation by 0.07% and 0.40%, respectively (Column 1, Table 4.5). This finding suggests that VF borrowers are from lower-income groups. Fongthong and Suriya (2014) state that near-poor households and lower-income households (with income above the poverty line) are more likely to participate in VFs. Likewise, Menkhoff and Rungruxsirivorn (2011) find that, though VFs reach lower-income households, commercial banks serve higher-income households. Kaboski and Townsend (2012) state that the VF programme can help poor people smooth their consumption levels.

An additional THB 1,000 increase in financial assets reduces a household's probability of participating in VFs by 0.0082% (Column 1, Table 4.5). Armendariz de Aghion and Morduch (2005) explain that financial assets (e.g., savings) can help rural households protect themselves against any disaster that may affect their income. In addition, income and assets provide an indication of a household's initial capital. A higher income level and/or assets reflects a less constrained household budget, which may weaken the demand for credit (Li, 2010; Ruiz-Tagle, 2005; Umoh, 2006).

The number of cars and motorcycles are significant in explaining VF participation. The results show that the number of cars is negative and significant at the 1% level. This indicates that an additional car in a household reduces a family's probability of participating in a VF by 3.70% (Column 1, Table 4.5). Rural Thai households understand the loan system because of BAAC loans; these households can access other financial services. Households with multiple cars can use them as collateral to access financial services (Fongthong & Suriya, 2014). The results show the coefficient of the number of motorcycles is positive and significant at the 1% level, indicating that if a household has an additional motorcycle, the household is more likely to borrow from a VF by 1%. Coleman (2006) explains that, during the off-farm season, most farm households engage in non-farm activities like petty trading and driving a motorcycle taxi. Households that use their motorcycles as taxis can borrow money for investment purposes. Households with a greater number of motorcycles are more likely to borrow money because motorcycles are important production inputs - like owning a house, they provide a way to earn additional income (Fongthong & Suriya, 2014).

All geographic factor coefficients have the hypothesized signs and are significantly associated with the probability of VF participation. The significant positive coefficients of central, north, northeast, and south imply that households living in these areas tend to have a higher probability of borrowing from VFs. In addition, the significant positive rural household coefficient suggests that households in rural areas are more likely to participate in VFs by 3.10% compared to other households (Column 1, Table 4.5). Mpuga (2008), who investigated accessibility and demand for credit in rural Uganda, finds

that location characteristics are important in the demand for credit. Households often use rural microcredit programmes to reduce their borrowing from informal sources. Fongthong and Suriya (2014) explain that the VFs provide loans throughout Thailand, meaning that rural households across the country are more likely to obtain loans. Menkhoff and Rungruxsirivorn (2011) find that VFs can help rural households reduce credit constraints.

The coefficient of difficulty in obtaining an emergency loan is negative and significant at the 1% level. This indicates that households that have difficulty in obtaining an emergency loan are less likely to borrow from VFs than households that have no trouble in obtaining an emergency loan. In fact, households that have trouble in obtaining an emergency loan are less likely to borrow from the VF by as much as 5.20%, all other factors being constant (Column 1, Table 4.5). This implies that most VF borrowers do not experience any difficulty accessing emergency loans. This finding illustrates that rural households in Thailand can access loans from both formal and informal financial sources and that these households can access financial services (loans, deposits, remittances, and insurance). In short, most VF borrowers do not have any difficulty in obtaining an emergency loan (Fongthong & Suriya, 2014); the VF programme is an alternative financial source for rural households.

4.2.5 The Determinants of SGPs Participation

Column 2, Table 4.5 indicates that SGP participation is significantly explained by: household head characteristics (age, female, education, single), demographics (household size, the dependency ratio, the number of children, the number of elderly), occupation (farmer, entrepreneur, formal worker, informal worker), income, expenditure, and assets (monthly income, financial assets, the number of cars, the number of motorcycles), and other variables (central, north, northeast, south, difficulty obtaining an emergency loan).

Age and single are negative and significant at the 1% level, whereas education and female are positive, significant predictors of SGP participation at the 1% and 5% levels, respectively. The household head's age influences the probability of SGP participation. With all other factors constant, a change in age decreases the probability of SGP participation by as much as 0.25% (Column 2, Table 4.5). This finding is the same as those of Mpuga (2008) and Li (2010) who state that younger individuals are more energetic, dynamic and can adapt to new technology better than older individuals. In short, younger individuals tend to save and/or borrow more for investment; older individuals are less inclined to save or borrow. Mohamed (2003) and Okurut (2006) state that the probability of borrowing from formal and semi-formal sources of credit decreases for older individuals. The significant negative sign at the 1% level for being single indicates that single household heads are less likely to participate in SGP. People who are single are less likely to be stable (in terms of responsibility); thus, lenders are less likely to view them as reliable (Mpuga, 2008;

Wachira & Kihiu, 2012). Therefore, they are less likely to access credit than their married counterparts.

The results show that well-educated household heads are more likely to borrow from SGPs. Holding all other determinants constant, the marginal effect of education indicates that an increase in the number of years of education of the household-head increases the probability of borrowing by 0.24% (Column 2, Table 4.5). A borrower's education reflects human capital that, in turn, facilitates participation in microfinance programmes (Li et al., 2011a; Mpuga, 2008; Tang et al., 2010). Previous studies argue that borrowers' education level is positively related to participation in microfinance programmes (Li et al., 2011a; Mpuga, 2008; Tang et al., 2010). Having a female household head is a significant positive predictor of SGP participation at the 10% level. The marginal effect of the female coefficient shows that the probability of being an SGP borrower increases by 0.17% if the borrower is female (Column 2, Table 4.5). As illustrated above, many microfinance programmes encourage women to borrow because they present a lower credit risk (Cull et al., 2016, 2018; Fongthong & Suriya, 2014).

Four demographic factors (household size, the dependency ratio, the number of children, and the number of elderly) are significant in explaining SGP borrowing status. The significant positive relationship between household size and microfinance participation indicates that larger households are more likely to participate in SGPs by 3.70% (Column 2, Table 4.5). This finding is like the VF result. Larger households have a higher probability of borrowing from microfinance programmes because these households have more income sources and, as a result, are more capable of repaying their loans (Fongthong & Suriya, 2014). Moreover, farm households are more likely to adopt agricultural loans as a risk management strategy; larger households use this money to expand their businesses (Nguyen, 2007; Saqib et al., 2016). Saqib et al. (2016) note that some farmers (large-scale farmers) have larger families because they live with extended family members and share the land. Agricultural credit plays a significant role in terms of farmers' income, production output, and food security, particularly for those vulnerable to floods, heavy rains, pests and diseases, and other catastrophic hazards (Saqib et al., 2016).

The coefficient of the dependency ratio is negative and significant at the 1% level. This indicates that households with a higher dependency ratio have a lower probability of borrowing from SGPs. This result is like the VF finding. The significant negative coefficients of the number of elderly and number of children at the 1% and 5% levels, respectively, indicate that if households have a greater number of elderly or dependent children, they are less likely to borrow from SGPs by 2.10% and 0.80%, respectively, compared to other households, all other factors held constant (Column 2, Table 4.5). This result indicates that households with a higher dependency ratio are less likely to borrow money

because they do not have the same ability to repay the loans. These households must spend greater amounts of money taking care of non-earning members, which likely affects their repayment ability (Fongthong & Suriya, 2014).

Column 2, Table 4.5 shows that farmers, entrepreneurs, formal workers, and informal workers are significant in explaining SGP borrowing. Households employed in farming, and those working in both formal and informal sectors, are less likely to borrow from SGPs by 3.80%, 1.90% and 3.10%, respectively, at the 1%, 5% and 1% significance levels, respectively. In contrast, households employed as entrepreneurs are more likely to borrow from SGPs, by 0.40% at the 10% significance level. These results suggest that, apart from farming, individuals who are entrepreneurs are the primary SGP borrowers. Luxchaigul (2014) states that SGP members are local people who regularly save money in their cash pool to invest in economic activities. Luxchaigul also explains that these loans would likely solve the no cash investment problem and illegal loans. SGPs can help borrowers solve their investment problems (Luxchaigul, 2014).

The expenditure and asset variables, monthly income, financial assets, the number of cars and number of motorcycles, are significant in explaining SGP participation. The results show that monthly income is positive and significant at the 1% level. The marginal effect of monthly income shows that every THB 1,000 increase in monthly income increases the probability of SGP participation by 0.02% (Column 2, Table 4.5). One possible explanation is that when households have more income and/or assets, they feel rich and consume more. As a result, they may also demand more credit (Cheng, 2006; Li, 2010; Ruiz-Tagle, 2005).

An additional THB 1,000 increase in financial assets reduces a household's probability of SGP participation by 0.0023% (Column 2, Table 4.5). The marginal effect of financial assets on SGP participation is minimal. Financial assets can help a rural household insure themselves against the likelihood of a natural disaster that may affect their income (Armendariz de Aghion & Morduch, 2005). These assets, which show a household's initial capital, reflect a less constrained household budget, which may weaken the demand for credit (Li, 2010; Ruiz-Tagle, 2005; Umoh, 2006).

The number of cars and of motorcycles are significant in explaining SGP participation. The results show that the number of cars is positive and significant at the 1% level. This indicates that an additional car in a household will increase a household's probability of SGP participation by 4.10% (Column 2, Table 4.5). Households that have multiple cars can use them as collateral to access financial services. Column 2, Table 4.5 also shows the coefficient of the number of motorcycles is positive and significant at the 1% level. This result indicates that an additional motorcycle will increase a household's probability of SGP participation by 2.10%. One reason why this may be so is that, during the off-farm season, most farm householders work in non-farm activities (Coleman,

2006). In short, for rural households, motorcycles are important production inputs (Fongthong & Suriya, 2014).

Almost all the geographic factor coefficients have the hypothesized signs and are significantly associated with the probability of SGP participation. The significant positive coefficients of central, north, northeast, and south imply that households in these areas have a higher likelihood of borrowing from SGPs (Column 2, Table 4.5). The results indicate that SGPs provide loans in all regions of Thailand and that these loans act as substitutes for informal credit (Akihiko, 2015). SGPs create a rural financial market using a bottom-up approach. SGPs serve as financial intermediaries by collecting savings from rural households and extending loans to their members (Akihiko, 2015).

Column 2, Table 4.5 also shows the coefficient of difficulty in obtaining an emergency loan is negative and significant at the 1% level. This indicates that households that have difficulty in obtaining an emergency loan are less likely to borrow from SGPs than households that do not have any problems. The significant negative difficulty in obtaining an emergency loan coefficient suggests that households that have trouble obtaining an emergency loan are less likely to participate in SGPs by 2.10%, compared to other households, all other factors held constant. This implies that most of SGP borrowers do not experience any difficulty gaining an emergency loan. The finding indicates that SGP borrowers can access both formal and informal financial services.

4.2.6 Both VF and SGPs Participation Determinants

The results in Column 3, Table 4.5, indicate that both VF and SGP participation is significantly explained by: household head characteristics (female, education, married, single), demographics (household size, the dependency ratio, the number of elderly people), occupation (farmer, entrepreneur, formal worker, informal worker), income, expenditure and assets (monthly expenditure on food and beverages, financial assets, the number of motorcycles), other variables (central, north, northeast, south, rural households, and difficulty obtaining an emergency loan).

The female and married coefficients are positive, significant predictors at the 1% level of both VF and SGP participation, whereas the education and single coefficients are negative, significant predictors at the 1% level. This indicates that household heads who are female borrow more from both VFs and SGPs than male household heads. The marginal effect of the female coefficient shows that the probability of being both a VF and SGP borrower increases by 0.45% when the borrower is female (Column 3, Table 4.5). A key objective of many microfinance programmes is to encourage women's participation; thus women are more likely to be granted loans (Cull et al., 2016, 2018). Moreover, MFI committees believe that female borrowers present a lower credit risk than men. Therefore, they have a higher chance of being granted loans than males (Fongthong & Suriya, 2014).

Column 3, Table 4.5, also shows that well-educated household heads are less likely to borrow from both VFs and SGPs. Holding all other determinants constant, the marginal effect of education indicates that an increase in the number of years of education of the household-head decreases the probability of borrowing by 0.07%. Thai microfinance programmes target poor and low educated borrowers (Fongthong & Suriya, 2014). Kasali et al. (2016), who examined the determinants that affect poor households' access to microfinance in Nigeria, find that microfinance programmes' borrowers have lower education levels.

The coefficient of married is positive and significant at the 1% level and the coefficient of single is negative and significant at the same level. The marginal effect of the married and single coefficients indicates that the probability of being both VF and SGP borrowers increases by 0.25% when the borrower is married and decreases by 0.80% when the borrower is single (Column 3, Table 4.5). The marital status finding is like the VF result. One possible explanation is that MFIs are more likely to grant loans to married individuals because they are believed to be more stable as they move from one life stage to another (Mpuga, 2008; Wachira & Kihui, 2012). Married people are thought to be more responsible and thus are seen as more trustworthy (Mpuga, 2008; Wachira & Kihui, 2012).

Three demographic-related factors (household size, the dependency ratio, and the number of elderly) are significant in explaining both the VF and SGP borrowing status. For household size, a significant positive relationship between household size and both VF and SGP participation shows that larger households are more likely to participate in both VFs and SGPs by 0.34% (Column 3, Table 4.5). This finding is like those of the other borrower groups (VF and SGP individual findings) where larger households have more income sources and, as a result, are more capable of repaying their loans (Fongthong & Suriya, 2014). Farm-households obtain loans to expand their businesses when their household size is larger (Nguyen, 2007; Saqib et al., 2016).

The coefficient of the dependency ratio is negative and significant at the 1% level indicating that households with higher dependency ratios have a lower probability of borrowing from both VFs and SGPs. The significant negative coefficient of the number of elderly at the 1% level indicates that if households have a greater number of elderly members, they are less likely to participate in both VF and SGP by 0.31% compared to other households, other factors held constant (Column 3, Table 4.5). This indicates that households with a higher dependency ratio are less likely to borrow because they do not have the same ability to repay their loans (Fongthong & Suriya, 2014).

Farmers, entrepreneurs, formal workers, and informal workers are significant factors in explaining borrowing from both VFs and SGPs. Households employed as farmers and entrepreneurs are more likely to borrow from both VFs and SGPs by 0.37% and 1.50%, respectively, at the 1% significance level. Households employed in formal and informal occupations are more likely to participate in both

VFs and SGPs by 0.82% and 0.50%, respectively, at the 1% significance level (Column 3, Table 4.5). These results suggest that farmers, entrepreneurs, formal workers, and informal workers are the primary borrowers from both VFs and SGPs. The finding indicates that both VFs and SGPs provide loans to farmers, entrepreneurs, formal workers, and informal workers. As noted earlier, these loans can solve the problem of no cash investments and illegal loans (Fongthong & Suriya, 2014; Lewis et al., 2013; Luxchaigul, 2014).

The expenditure and assets variables, monthly expenditure on food and beverages, financial assets, and the number of motorcycles, are significant in explaining both VF and SGP participation. For the monthly expenditure on food and beverages, the negative coefficient is significant at the 5% level. The marginal effect of monthly expenditure on food and beverages shows that every THB 1,000 increase in monthly expenditure on food and beverages decreases the probability of both VF and SGP participation by 0.02% (Column 3, Table 4.5). This suggests that both VF and SGP borrowers are from lower-income groups. One possible explanation is that poor rural households need credit to maintain their consumption levels (especially for necessities like food) when faced with a cash shortage (Li, 2010). In developing countries, the poor usually rely on credit to smooth their consumption expenditure (Doan et al., 2010).

An additional THB 1,000 increase in financial assets reduces a household's probability of participating in both VFs and SGPs by 0.0017% (Column 3, Table 4.5). The marginal effect of financial assets on both VF and SGP participation is minimal. Financial assets may help a rural households overcome situations that may affect their income (Armendariz de Aghion & Morduch, 2005). In addition, financial assets show a household's capital. In short, more financial assets reflect a less constrained household budget, which may reduce the demand for credit (Li, 2010; Ruiz-Tagle, 2005; Umoh, 2006).

The number of motorcycles is significant in explaining both VF and SGP participation. Column 3, Table 4.5 shows the coefficient of the number of motorcycles is positive and significant at the 1% level, indicating that an additional motorcycle in a household increases that household's probability of participating in both VFs and SGPs by 0.25%. One possible explanation is that motorcycles, which are an important input component, are used in non-agricultural activities during the off-farm season (Coleman, 2006). Rural households use their own vehicles as production inputs to invest in new businesses (Fongthong & Suriya, 2014).

All geographic factor coefficients have the hypothesized signs and are significantly associated with the probability of both VF and SGP participation. The significantly positive coefficients of central, north, northeast, and south imply that households in these areas have a higher likelihood of borrowing from both VFs and SGPs. In addition, the significant positive rural household coefficient

suggests that households in rural areas are more likely to participate in both VFs and SGPs by 0.18%, compared to other households (Column 3, Table 4.5). This mirrors earlier results for VF and SGP borrowers. These programmes provide loans that help rural Thai households decrease their reliance on informal credit (Mpuga, 2008).

Column 3, Table 4.5, also shows that the coefficient of difficulty in obtaining an emergency loan is negative and significant at the 1% level. This indicates that households that have difficulty in gaining an emergency loan are less likely to borrow from both VFs and SGPs than households that have no difficulty. The difficulty in obtaining an emergency loan's coefficient suggests that households that have difficulty in accessing an emergency loan are less likely to participate in both VFs and SGPs by 0.42% compared to other households, all other factors held constant. This implies that both VF and SGP borrowers do not have trouble obtaining an emergency loan.

In summary, the results reveal that VFs tend to service low-income households in rural areas. Most VF borrowers do not have difficulty accessing loans. In addition, older, lower educated, female household heads are more likely to gain loans. Larger households and those with lower dependency ratios are more likely to participate in VFs. The VF primary borrowers are farmers, entrepreneurs, formal and informal workers. Young household heads in all Thailand's regions are more likely to borrow from SGPs. Those with higher education levels and those with greater income tend to exhibit higher levels of SGP participation. Most SGP borrowers can access other loans. Finally, those with low education levels, married household heads, and female household heads are more likely to borrow from both VFs and SGPs. Larger households have a higher probability of borrowing from both microfinance programmes. Farmers, entrepreneurs, formal workers, and informal workers are the main borrowers of both VFs and SGPs. Borrowers in this group live in rural areas and can access other loan sources. The next section discusses the impact of microfinance programme participation on economic and social welfare.

4.3 The Impact of VF and SGP Participation on Economic and Social Welfare

Borrower welfare is measured in terms of monthly household income and consumption. The impact of a microfinance programme is subject to two main sources of bias: observed and unobserved biases. In this study, we use PSM and panel data to evaluate the microfinance programme impact. We use cross-sectional data from the SES Survey (2017) and panel data from the SES Survey conducted in 2012 and 2017. Sections 4.3.1 and 4.3.2 discuss the empirical results from the PSM and panel data, respectively.

4.3.1 Microfinance Impact: PSM Impact Evaluation

4.3.1.1 Data for Impact Evaluation

The data for VF and SGP impact evaluation were collected by the National Statistical Office, the Ministry of Information and Communication Technology (see section 4.1). The impact assessment compares outcomes for both borrowers (treated group) and non-borrowers (control group). The treated group is the target group. This group was selected based on the borrowing status under credit constraints. The control group consists of non-borrowers who may or may not confront credit constraints. To evaluate the economic and social welfare impact, this section uses monthly household income and expenditure to measure outcomes.

4.3.1.2 Estimation Strategies

The coefficient of the mean impact of treatment on δ_{PSM}^{ATT} is obtained using the PSM method based on the following specification:

$$\delta_{PSM}^{ATT} = E(y_1|T = 1, x) - E(y_0|T = 0, x) \quad (4.4)$$

Where y_1, y_0 : are the potential outcomes in the two counterfactual situations (i.e., participation/non-participation in the microfinance programme). The outcomes in this study are household monthly income and expenditure (measured in THB 1,000). T is a binary variable; if a household participates in a microfinance programme ($T=1$) or if not ($T=0$). X is a covariate set of observed characteristic variables, including household head characteristics (female, education, married, single), demographics (household size, the dependency ratio, the number of children, the number of elderly), socio-economic factors such as occupation (farmer, entrepreneur, formal worker, informal worker), income and assets (homeowner, landless, financial assets, the number of cars, the number of motorcycles), other variables (central, north, northeast, south, rural households, difficulty obtaining an emergency loan). Household income and consumption in 2017 are included in the covariate to explain the microfinance programme impact estimator of each outcome of interest. Covariate variables chosen from the previous section have high predictive power of credit participation (equation 4.2) conditional on the explanatory variables.

Covariates are used to control for individual heterogeneity and are selected following the rule that the variable should simultaneously influence microfinance programme participation and the outcome (Caliendo & Kopeinig, 2008; Phan, 2012). Therefore, in this study, covariates are selected from variables that are significant in determining microfinance programme participation in the previous section. These variables have been found to be correlated with income and consumption outcomes in other empirical studies. For example, in terms of household characteristics, household size and education are strongly correlated with income and consumption outcomes in microfinance

studies (see Nguyen, 2008; Phan 2012). Covariates act as a control for individual heterogeneity since the borrowers are not a random group of participants. Covariates also assume that households are time-invariant during the income and consumption period. If the conditions are satisfied, impact estimators are obtained using different matching procedures (Caliendo & Kopeinig, 2008; Phan, 2012).

The matching procedure follows a particular process. First, the variables are selected to define the probability of microfinance participation. These variables include household head characteristics (female, education, married, single), demographics (household size, the dependency ratio, the number of children, and the number of elderly), socio-economic factors such as occupation (farmer, entrepreneur, formal worker, informal worker), income and assets (homeowner, landless, financial assets, the number of cars, and the number of motorcycles), other variables (central, north, northeast, south, rural households, and difficulty gaining an emergency loan). The next step uses the probit model (see equation 3.24, section 3.2.2.1) to calculate the probability of microfinance participation. Then, propensity scores are calculated based on this probability. Balancing tests are conducted to ensure that the mean propensity score is not different for the treated and control groups in each block for each model (Caliendo & Kopeinig, 2008; Phan, 2012). This process ensures that a comparison group is constructed from the selected variables. If balancing is satisfied, common support is defined. Common support is then used for the matching. Finally, I estimate the microfinance impact.

4.3.1.3 Results and Discussion

VF Impact on Income and Expenditure (Housing, Food, Medicine, Education, and Transport)

The estimated results of the probit model (equation 3.24, section 3.2.2.1) for propensity scores are reported in Table 4.6. Among the factors determining the probability of participation in the VF, female, education, married, household size, farmer, entrepreneur, formal worker, informal worker, central, north, northeast, south, and rural households are significant at the 1% level. The dependency ratio is significant at the 5% level. The Chi-square test for this model shows statistical significance at the 1% level, indicating that the variables included in this model statistically explain the propensity scores used in the matching steps.

The propensity scores for each covariate were estimated based on the results of the probit model (see equation 3.24, section 3.2.2.1). This model was balanced based on the results of the balancing tests. Table 4.7 shows that all the covariates are well balanced because the t-test for equality of means in both the treated and control groups is non-significant after matching and the percentage bias of all covariates when matched is less than 5%.

Table 4.6 The Probit Results for the Propensity Score for the VF Impact on Income and Expenditure on Housing, Food, Medicine, Education and Transport

Control Variable	VF	
	Coefficient	S.E.
Constant	-3.006***	0.134
Household Head Characteristic		
Female (yes=1)	0.210***	0.018
Education (year)	-0.061***	0.003
Married (yes=1)	0.229***	0.020
Demographic		
Household Size (persons)	0.091***	0.006
Dependency Ratio	0.069**	0.035
Occupation		
Farmer (yes=1)	0.692***	0.020
Entrepreneur (yes=1)	0.227***	0.053
Formal Worker (yes=1)	0.335***	0.030
Informal Worker (yes=1)	0.313***	0.028
Other		
Central (yes=1)	1.322***	0.130
North (yes=1)	1.688***	0.130
Northeast (yes=1)	1.786***	0.130
South (yes=1)	0.635***	0.132
Rural Household (yes=1)	0.202***	0.016
Number of Obs.	41,099	
Log Likelihood	-16434.986	
LR chi2(14)	9558.93	

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

Figure 4.1 demonstrates the density of propensity scores estimated for the impact of VFs. The solid and long dash lines in Figure 4.1 graphically illustrate the distribution of the propensity scores of borrowers and non-borrowers, respectively. The propensity scores range from 0.0015352 to 0.8204954 and from 0.0000411 to 0.8346302 for borrowers and non-borrowers, respectively. The mean scores are 0.388622 and 0.1635417 for borrowers and non-borrowers, respectively. The figure shows that the model performs well in separating treatment and control groups because the maximum density of the propensity score for the treatment group is always significantly higher than the maximum density of propensity score for the control group (Cintinna & Love, 2014). Given a substantial overlap in distributions, the common support region is defined in the range of 0.0000411 to 0.8346302. The figure also shows that there is sufficient common support; this can be seen in the area of overlap between the two densities. This common support guarantees that the treatment observations can be matched with comparison observations. In this process, no treatment observations are dropped because of a lack of comparison units (Cintinna & Love, 2014).

Table 4.7 The Balancing Test for the Propensity Score for the VF Impact on Income and Expenditure (Housing, Food, Medicine, Education and Transport)

Control Variables	p-Value of t-Test Before Matching	p-Value of t-Test After Matching	% Bias After Matching
Household Head Characteristic			
Female (yes=1)	0.000	0.414	1.2
Education (year)	0.000	0.532	0.7
Married (yes=1)	0.000	0.791	-0.4
Demographic			
Household Size (persons)	0.000	0.109	2.4
Dependency Ratio	0.000	0.315	1.3
Occupation			
Farmer (yes=1)	0.000	0.717	-0.6
Entrepreneur (yes=1)	0.000	0.419	1.1
Formal Worker (yes=1)	0.000	0.332	1.3
Informal Worker (yes=1)	0.000	0.182	-2.1
Other Variables			
Central (yes=1)	0.000	0.713	0.5
North (yes=1)	0.000	0.881	0.2
Northeast (yes=1)	0.000	0.715	-0.6
South (yes=1)	0.000	0.939	-0.1
Rural Households (yes=1)	0.000	0.939	-0.1

Source: Author's calculations

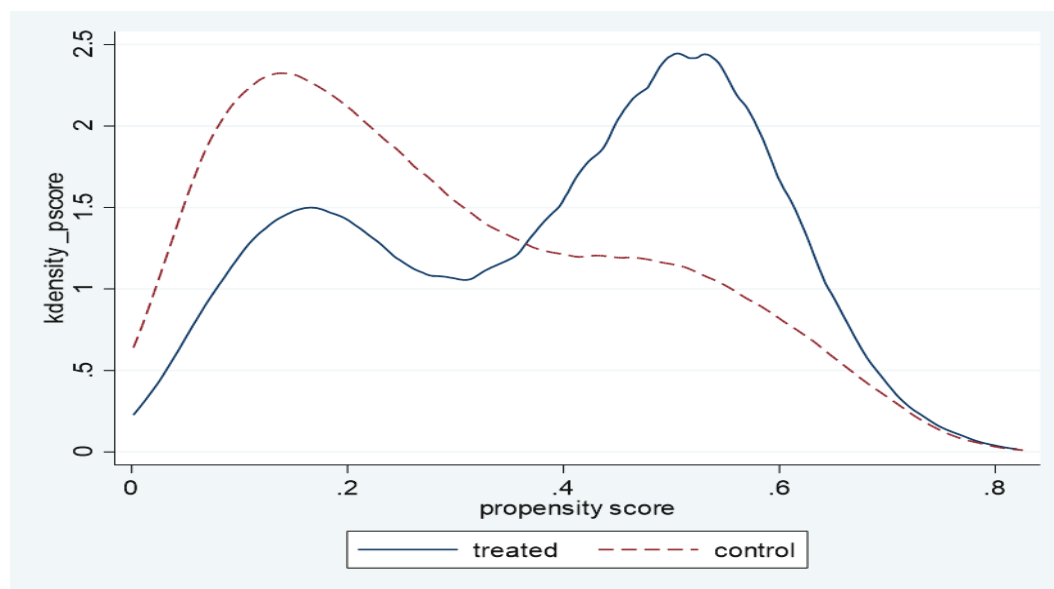


Figure 4.1 Propensity Score for Borrowing Status based on the Covariates for the Impact of VFs on Income and Expenditure (Housing, Food, Medicine, Education and Transport)

Source: Author's calculations

The estimates of the average treatment effect of VF programme participation on the treated (ATT) are reported in Table 4.8 for six outcomes using nearest neighbour matching. The first column in

Table 4.8 specifies the outcome variables in the propensity score function and the second and the third columns report the treated and control in relation to the mean of income and expenditure. The last column shows the ATT for household monthly income and expenditure by nearest neighbour matching; the standard errors are provided in parentheses. According to these PSM estimates, the average income of VF borrowers is less than non-borrowers, by 3,037 baht. On average, borrowers spent 99 baht less on education and 63 baht less on transport per month than non-borrowers. This comparison is based on data from 8,700 borrowers and 32,399 non-borrowers. Matching results are statistically significant at the 5% level for income and educational expenditure and transport expenditure is statistically significant at the 10% level. Housing, food, and medical expenditure are not statistically significant.

Table 4.8 Average Treatment Effect of VFs on Monthly Income and Expenditure using Matching Estimator

	VF Participation	Control	Difference
Mean Income	18.568	21.605	-3.037** (1.242)
Mean Housing Expenditure	1.970	2.097	-0.127 (0.125)
Mean Food Expenditure	6.453	6.757	-0.304 (0.187)
Mean Medicine Expenditure	0.334	0.309	0.025 (0.066)
Mean Education Expenditure	0.160	0.259	-0.099** (0.045)
Mean Transport Expenditure	0.122	0.185	-0.063* (0.038)

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

The PSM results reveal that the impact of VFs is significant in terms of income, educational, and transport expenditure but not for housing, food, and medical expenditure. However, the sign of these variables is negative. This result is like Diagne and Zeller's (2001) study of Malawi, where the authors evaluated the impact of microfinance programmes on income and household food security. They find that there are significant negative impacts on the per capita income of borrowers. Diagne and Zeller (2001) explain that borrowers in Malawi use their loans in low-income crops, therefore, their income decreases because of low crop price. Farmers also confront disasters such as drought, leading to decreased income. Abou-Ali et al. (2010) assessed the Social Fund for Development (SFD) programmes in Egypt using PSM. The authors find that non-farm income decreases because borrowers invest loans in farming; they often stop doing paid work outside the farm. Chandoevrit and Ashakul (2008) evaluated the impact of the VF on household income in Thailand. Their results show that the VF increases farm income only in the central region, not in other regions. The authors

state that the VF does not decrease the country's poverty. This programme increases only non-consumption expenditure (e.g., expenditure on gifts, donations, gambling, insurance premiums, taxes, and interest payments), indicating that borrowers do not spend their loans on investment activities. Any positive impact on farm income is inadequate in terms of improving total household income.

The expenditure result is similar to that in Waelde's (2011) study. Waelde (2011) evaluated the impact of microcredit expenditure in India and finds a significant negative impact on expenditure for the very poor. Poor entrepreneurs are cannot make significant financial gains because they are unable to accumulate more than a certain level of wealth above which they could shift private expenditure into business activities. The author recommends adjusting programmes to fit specific groups of entrepreneurs and their needs. Augsburg et al. (2015) evaluated the impact of microfinance programmes on income and expenditure in Bosnia and Herzegovina. Augsburg et al. (2015) find that there is a significant decrease in weekly consumption and savings. The authors explain that households invest all their loans in their businesses (on start-up costs) because they have limited investment capital. These households may need to decrease consumption and/or accumulate more savings if the total loan does not cover the required capital; hence they face liquidity constraints.

SGP Impact on Income and Expenditure (Housing, Food, Medicine, Education, and Transport)

The estimated results of the probit model (equation 3.24, section 3.2.2.1) for propensity scores are reported in Table 4.9. Among the factors determining the probability of participation in SGPs, female, education, married, household size, the dependency ratio, farmer, entrepreneur, formal worker, informal worker, central, north, and south are significant at the 1% level. The northeast variable is significant at the 5% level. The Chi-square test for this model shows statistical significance at the 1% level, indicating that the variables included in this model statistically explain the propensity scores used in the matching steps.

Based on the results of the probit model (equation 3.24, section 3.2.2.1), the propensity scores for each covariate were estimated. This model was based on balancing tests. Table 4.10 shows all the covariates are well balanced; the t-test for equality of means in treated and control groups is non-significant after matching and percentage bias of all covariates when matched is less than 5%.

Table 4.9 The Probit Results for the Propensity Score for the SGP Impact on Income and Expenditure (Housing, Food, Medicine, Education and Transport)

Control Variable	SGPs	
	Coefficient	S.E.
Constant	-2.006***	0.049
Household Head Characteristic		
Female (yes=1)	0.063***	0.018
Education (year)	0.028***	0.002
Married (yes=1)	0.113***	0.020
Demographic		
Household Size (persons)	0.198***	0.006
Dependency Ratio	-0.603***	0.035
Occupation		
Farmer (yes=1)	-0.157***	0.023
Entrepreneur (yes=1)	0.250***	0.021
Formal Worker (yes=1)	0.189***	0.026
Informal Worker (yes=1)	-0.108***	0.026
Other Variables		
Central (yes=1)	0.255***	0.037
North (yes=1)	0.142***	0.039
Northeast (yes=1)	0.087**	0.039
South (yes=1)	0.266***	0.040
Rural Households (yes=1)	-0.004	0.018
Number of Obs.	41,099	
Log Likelihood	-15766.171	
LR chi2(14)	2759.79	

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

Figure 4.2 demonstrates the density of propensity scores estimated for the impact of SGPs. The solid and long dash lines in Figure 4.2 illustrate the distribution of the propensity scores of borrowers and non-borrowers, respectively. The propensity scores range from 0.0168422 to 0.8383503 and from 0.0085819 to 0.7965991 for borrowers and non-borrowers, respectively. The mean scores are 0.2023521 and 0.1369062 for borrowers and non-borrowers, respectively. The figure shows that the model performs well in separating treatment and control groups because the maximum density of propensity scores for the treatment group is always significantly higher than the maximum density of propensity score for the control group (Cintinna & Love, 2014). Given a substantial overlap in distributions, the common support region is defined in the range of 0.0085819 to 0.8383503. The figure also shows that there is sufficient common support, which can be seen in the area of overlap between the two densities. This common support guarantees the treatment observations can be matched with comparison observations. In this process, no treatment observations were dropped because of a lack of comparison units (Cintinna & Love, 2014).

Table 4.10 The Balancing Test for the Propensity Score for the SGP Impact on Income and Expenditure (Housing, Food, Medicine, Education and Transport)

Control Variable	p-Value of t-Test Before Matching	p-Value of t-Test After Matching	% Bias After Matching
Household Head Characteristic			
Female (yes=1)	0.000	0.231	2.2
Education (year)	0.000	0.532	-1.2
Married (yes=1)	0.000	0.144	-2.5
Demographic			
Household Size (persons)	0.000	0.359	1.8
Dependency Ratio	0.000	0.381	1.4
Occupation			
Farmer (yes=1)	0.000	0.246	2.0
Entrepreneur (yes=1)	0.000	0.751	0.6
Formal Worker (yes=1)	0.000	0.169	-2.6
Informal Worker (yes=1)	0.000	0.155	-2.6
Other Variables			
Central (yes=1)	0.000	0.219	2.3
North (yes=1)	0.000	0.871	0.3
Northeast (yes=1)	0.000	0.643	-0.8
South (yes=1)	0.000	0.411	-1.6
Rural Households (yes=1)	0.001	0.139	2.7

Source: Author's calculations

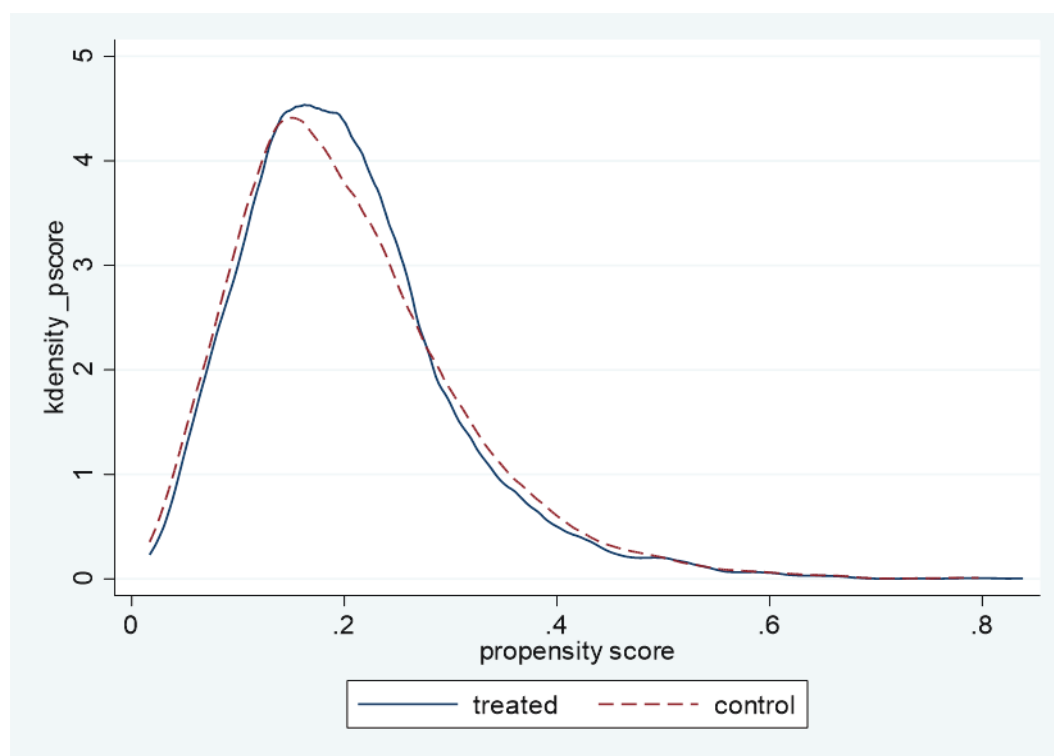


Figure 4.2 Propensity Score of Borrowing Status based on the Covariates for the Impact of SGPs on Income and Expenditure (Housing, Food, Medicine, Education and Transport)

Source: Author's calculations

The estimates of the average treatment effect of SGP programme participation on the treated (ATT) are reported in Table 4.11 for six outcomes using nearest neighbour matching. The first column in Table 4.11 specifies the outcome variable in the propensity score function. The second and the third columns report the mean of income and expenditure of the treated and control groups. The last column shows the ATT for household monthly income and expenditure by nearest neighbour matching; the standard errors are provided in parentheses. According to these PSM estimates, the average income of SGPs borrowers is 2,620 baht more than non-borrowers. The matching results are statistically significant at the 5% level. This comparison is based on matching 6,035 borrowers and 35,064 non-borrowers.

Table 4.11 The Average Treatment Effect of SGPs on Monthly Income and Expenditure using a Matching Estimator

	SGP Participation	Control	Difference
Mean Income	36.406	33.787	2.620** (1.249)
Mean Housing Expenditure	2.876	2.951	-0.075 (-0.47)
Mean Food Expenditure	8.962	8.969	-0.007 (0.136)
Mean Medicine Expenditure	0.640	0.528	0.112 (0.096)
Mean Education Expenditure	0.453	0.499	-0.046 (0.038)
Mean Transport Expenditure	0.528	0.542	-0.013 (0.040)

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

The PSM results reveal that the impact of SGPs is significant on income but not significant on expenditure. The income result is similar to that in Li et al.'s (2011b) study that evaluated the impact of individual loans from Rural Credit Cooperatives on income in China. The authors find that the impact of Rural Credit Cooperatives on income is significant because households that obtain loans from microcredit programmes invest in income-generating activities, e.g., agricultural production and self-employment. This investment can improve their livelihood. Dadson, Abankwah, and Kwansah (2012) evaluated the impact of a microcredit programme in Ghana and find that female borrowers have a statistically significant higher income than the control group. The authors state that microcredit provides a means to improve women's income in small scale businesses.

The results show that the microfinance programme's impact on expenditure is insignificant. This indicates that individuals or households participating in microfinance programmes have insignificant gains in terms of consumption over non-participants. The results are similar to those in Crépon et al.

(2015) and Banerjee et al.'s (2015) studies. Crépon et al. (2015) find that the microcredit impact on expenditure is insignificant. They explain that it is possible that most borrowers have only just received their loans and therefore the impact of microfinance programmes is limited. In their study of microcredit in India, Banerjee et al. (2015) find that the impact of the loans on expenditure is insignificant. They explain that by the fact that microcredit loans are substitutes for informal loans.

Though PSM is a useful method for controlling bias because of observed determinants in impact evaluation, Marr (2012) argues that PSM cannot control unobserved characteristics (such as individual motivation and ability) that affect microfinance participation. The method is more appropriate for cross-sectional survey data (Dehejia & Wahba, 2002). Smith and Todd (2005) and Dehejia (2005) state that there are two concerns relating to PSM. First, cross-sectional data cannot control for unobserved characteristics (such as individual motivation and ability) or time effects. Secondly, bias, which is associated with cross-sectional data matching estimators, may be too large if there is no good set of covariates or if treated and control individuals or households are not strictly comparable to those located in different markets (Smith & Todd, 2005). Panel data can control for unobserved bias, but the data must be available. The next section discusses microfinance programme estimation using panel data.

4.3.2 Microfinance Impact: Impact Evaluation of Panel Data

4.3.2.2 Data for Microfinance Impact Evaluation

As previously noted, this study evaluates the impact of microfinance programmes in Thailand using panel data from SES surveys in 2012 and 2017 collected by the National Statistical Office of the Ministry of Information and Communication Technology. Briefly, the 2017 survey interviewed 4,461 households across the country. Data were collected monthly. The information includes a variety of household socio-economic data, such as income, expenses, assets, and liabilities. The 2012 survey used the same questionnaire but covered 6,080 households. The sample used in this study includes 4,406 households (both borrowers and non-borrowers) throughout the country in panel data drawn from the 2017 SES survey. Of the 4,406 households, 353 (8.01%) borrowed from VFs, 49 (1.11%) borrowed from SGPs, and 4,004 (90.88%) were non-borrowers. These data include information about borrowers/non-borrowers ages, level of education, household size, dependency ratio, monthly income, assets, number of cars, number of motorcycles, marital status, occupation, and the household location. Table 4.12 summarises the variables used in the impact evaluation model (equation (4.5)).

Panel data are used to estimate the unbiased microfinance programme impact. Two years' data were collected, before and after programme implementation. In other words, we required baseline data before VFs and SGPs were officially established and one period after these microfinance programmes

were formed. However, our first dataset was collected in 2012 when the microfinance programmes were already established. Nguyen (2008) and Phan (2012) raised concerns about bias when evaluating microfinance programmes using only post-programme data because there may be significant differences between the treated and the control groups in the first period. Therefore, the data are adjusted before we use the panel data.

Table 4.12 Borrower and Non-borrower Characteristics using Panel Data from the SES Survey (2017)

	Non-borrower	VF Borrower	SGP Borrower
Household Head Characteristic			
Age (years)	58.20	55.98	51.41
Female (yes=1)	0.39	0.34	0.43
Education (years)	7.70	6.62	7.66
Married (yes=1)	0.66	0.80	0.74
Single (yes=1)	0.08	0.04	0.02
Demographic			
Household Size (persons)	3.88	4.29	4.80
Dependency Ratio	0.50	0.40	0.45
Occupation			
Farmer (yes=1)	0.23	0.46	0.34
Entrepreneur (yes=1)	0.14	0.07	0.21
Formal Worker (yes=1)	0.22	0.17	0.23
Informal Worker (yes=1)	0.05	0.07	0.04
Income and Assets			
Monthly Income (THB 1,000)	17.30	8.62	13.05
Landless (yes=1)	0.63	0.23	0.56
Assets (THB 1,000)	865.54	567.88	506.43
Number of Cars	0.25	0.11	0.24
Number of Motorcycles	1.20	1.63	1.76
Other Variables			
Central (yes=1)	0.22	0.15	0.18
North (yes=1)	0.19	0.31	0.31
Northeast (yes=1)	0.30	0.53	0.22
South (yes=1)	0.13	0.003	0.20
Rural Households	0.50	0.69	0.47
Total	4,004	353	49

Source: Author's calculations

4.3.2.2 Estimation Strategies

To deal with the data problem, PSM is estimated for the first time to match borrowers with non-borrowers, using a set of observable characteristics. This estimation creates a new panel dataset, consisting of borrower and non-borrower groups that have similar observed characteristics. The objective of this step is to eradicate observed heterogeneity in the initial period before using the panel data model (Heckman et al., 1997).

Panel data are used to solve unobserved variable bias when measuring the impact of VFs and SGPs, because panel data can eliminate unobserved variable bias (Boonperm et al., 2013). This study uses the fixed effect model to evaluate the impact of VFs and SGPs in Thailand. The fixed effect model corrects any possible bias because of pre-existing initial heterogeneity of households and time-variance factors (Imai & Azam, 2012).

Given the matched pre-programme attributes from PSM and under the exogeneity of microfinance programme participation, the microfinance programme impact estimator can be obtained from equation (3.29) (Section 3.2.2.2). That model is rewritten as follows:

$$y_{it} = \alpha_i + X_{it}\beta + T_{it}\gamma + YEAR_t\phi + \varepsilon_{it} \quad (4.5)$$

Where y_{it} indicates the outcome variables of interest, e.g., household income and consumption, for household i at time t ($t= 2012, 2017$), X_{it} is a set of regressors that are the observed household characteristics, such as gender of the household head, age of the household head, the number of household members, education, careers, the value of house and landholding. T_{it} is a programme participation dummy variable which takes the value of 1 if the individual or household i takes a loan from a microfinance programme in time t and 0 otherwise. $YEAR_t$ is a vector of year dummy that takes into account time-specific effects, α_i indicates unobserved characteristics of the household and ε_{it} are error terms.

4.3.2.3 Results and Discussion

This section discusses the impact of VF and SGP participation on the income and expenditure of borrowers. Tables 4.13 and 4.14 summarise the estimated results of the fixed effects with PSM models. Table 4.13 outlines the VF impact on income and expenditure and Table 4.14 includes the SGP impact on income and expenditure.

VF Impact on Income

The second column in Table 4.13 shows that the household head education level, household size, and formal worker, are positive and significant at the 1% level. Informal worker is positive and significant at the 5% level. These results reveal that an additional year's education, a larger household, and formal and informal workers have higher monthly incomes: 445 baht, 3,793 baht, 3,463 baht and 3,694 baht, respectively. However, the dependency ratio, farmer, entrepreneur, and assets are negative and significant at the 1% level. The negative coefficient of these variables indicates that a higher dependency ratio, farmer, entrepreneur, and higher assets have a lower monthly income: 9,238 baht, 4,390 baht, 4,950 baht, and 2.83 baht, respectively.

The impact estimator on household income is not significant. This result is similar to Chandoevmit and Ashakul's (2008) study. They evaluated the impact of the VF on household income in Thailand. They find that the VF does not decrease the country's poverty. They also find that this programme increases only non-consumption expenditure, which indicates that borrowers do not spend their loans on investment activities. Instead, borrowers spend the money on things such as household necessities.

VF Impact on Housing Expenditure

The third column in Table 4.13 shows that households with a female household head, household size, assets, farmer, and formal worker are positive and significant at the 10% level. This indicates that female household heads, larger households, greater assets, farmer, and formal worker have higher monthly housing expenditure: 322.56 baht, 159.91 baht, 0.1 baht, 191.65 baht, and 243.54 baht, respectively. However, the dependency ratio and the year 2017 are negative and significant at the 1% and 5% level, respectively. This result suggests that a higher dependency ratio and the year 2017 have lower monthly housing expenditure: 488.85 baht and 137.47 baht, respectively.

The impact of the VF on housing expenditure is not significant. This result is similar to Li's (2010) study that evaluated microcredit in China. Li finds that microcredit's impact on house repairs or construction is not statistically significant. Cintina and Love (2014) evaluated microfinance impact on expenditure for MFI borrowers in India and explain that microfinance loans can be used for small home repairs. However, they do not find any difference in housing expenditure between borrowers and non-borrowers.

VF Impact on Food Expenditure

The fourth column in Table 4.13 shows that household size and formal workers are positive and significant at the 5% level. This shows that larger households and formal workers have higher monthly food expenditure: 847.22 baht, and 1,708.60 baht, respectively. However, the coefficient of the dependency ratio is negative and significant at the 1% level. This indicates that households with a higher dependency ratio have a lower monthly food expenditure: 3,864.30 baht.

The impact estimator for a household's food expenditure is not significant. This is similar to Banerjee et al.'s (2015) result. They evaluated microcredit programmes in India and find that microcredit programmes in India do not affect food expenditure. Similarly, Augsburg et al. (2015) evaluated the impact of microfinance programmes on food consumption in Bosnia and Herzegovina. The authors find that microfinance programmes do not increase weekly food consumption. They explain that households who establish businesses often do not have enough money to cover their start-up costs. Therefore, these households must reduce their household consumption to cover these costs. Thai rural households do not save enough to invest in their businesses. Thai farmers obtain loans to invest

in farming and then use their harvest income to repay the loans (Hickson, Pochanukul, & Achavanuntakul, 2013).

VF Impact on Medical Expenditure

The fifth column in Table 4.13 shows that the year 2017, female household heads, and the dependency ratio are positive and significant at 1%, 5%, and 10% levels, respectively. These results reveal that the year 2017, female household heads and those with a higher dependency ratio have higher monthly medical expenditure: 1,285.28 baht, 2,006.11 baht, and 2,084.67 baht, respectively.

The VF impact on medical expenditure is not significant. Microfinance is a short-term loan that is typically used as a substitute for informal loans (Banerjee et al., 2015; Crépon et al., 2015).

Moreover, the main objective of the VF is to help the lowest income groups to improve their investments, job creation, income generation, welfare and reduce expense (Fongthong & Suriya, 2014). This result indicates that the VF's primary objective is not to improve health expenditure.

VF Impact on Educational Expenditure

The sixth column in Table 4.13 shows that entrepreneurs and the year 2017 are positive and significant at the 1% level; household size and farmers are positive and significant at the 5% level. These results reveal that entrepreneurs, the year 2017, a larger household, and farmers have higher monthly educational expenditure: 705.65 baht, 569.98 baht, 213.91 baht, and 507.37 baht, respectively. However, the coefficient of informal worker is negative and significant at the 1% level. This result shows that informal workers have lower monthly educational expenditure of 1,370.63 baht.

The impact of VFs on educational expenditure is positive and significant at the 1% level. The result also reveals that VF borrowers spend 585.03 baht more on education than non-borrowers. This result is similar to Takahashi, Higashikata, and Tsukada's (2010) result. They evaluated the impact of microcredit programmes in Indonesia and find that there is a significant, positive short-term impact on clients' school expenditure. They explain that the poor benefit more from microcredit participation via investment in their children's schooling. Money spent on education helps to break the poverty vicious circle. Adjei, Arun, and Hossain (2009) evaluated the role of Ghanaian microfinance programmes in asset-building and poverty reduction and find that borrowers often use the loans to improve their children's education.

VF Impact on Transport Expenditure

The seventh column in Table 4.13 indicates that education and household size are positive and significant at the 1% level. This result shows that a higher education level and larger household have a higher monthly transport expenditure, 148.21 baht and 864.76 baht, respectively. However, the

year 2017, the dependency ratio and assets are negative and significant at 1%, 5% and 5% levels, respectively. This shows that 2017, a higher dependency ratio, and larger assets have lower monthly transport expenditure, by 532.60 baht, 838.28 baht, and 0.26 baht, respectively.

The VF impact on transport expenditure is not significant. Our result implies that VF loans do not increase a household's transport expenditure. Vehicles can help households in many ways. For example, households can transport products from remote areas to the shops and markets. In addition, they can drop off and pick up their children from school (Awan & Juiya, 2015). Vehicles are an important production input and provide a means to travel to work (Kaboski & Townsend, 2012). This implies that transport expenditure is related to household production. Therefore, as our result implies, VF loans are not related to household production in rural areas.

VF participation does not affect a borrowers' income and, apart from educational expenditure, all other forms of expenditure. This result indicates that VF participation does not help borrowers improve their income or encourage them to spend more on food or healthcare. However, VF loans can increase borrowers' educational expenditure. This result suggests that VFs help some borrowers invest in the education of their children. Fongthong (2013) states that VFs contribute to households' educational expenditures. Borrowers in the Thai agricultural sector do not have any income outside of the planting season. If they do not have any savings, they must rely on loans to pay for large expenses such as tuition fees. VFs can help them meet this financial need (Yostrakul, 2018). An ADB study concludes that 14% of Thai adults use loans for educational expenditure (Microfinance Services, Ltd., 2013). Thai people feel a great sense of responsibility to invest in their children's education. Thai parents believe that when their children graduate, they will find a good job and have a better life (Fongthong, 2013).

SGP Impact on Income

The second column in Table 4.14 indicates that education and household size are positive and significant at the 5% level. This result shows that an increase in the years of a household head's education and larger households have higher monthly income of 896.26 baht and 3,144.99 baht, respectively. Mpuga (2008) notes that educated borrowers are more likely to have higher incomes and savings and therefore to have assets that can be used as collateral. Larger households tend to have higher incomes because they have more income sources (Fongthong & Suriya, 2014).

In contrast, the dependency ratio and entrepreneur are negative and significant at the 1% level. The farmer variable is also negative but significant at the 5% level. The negative coefficient of these variables indicates that households with higher dependency ratios, entrepreneurs and farmers have lower incomes than other households. The result reveals that a higher dependency ratio significantly decreases monthly household income by 20,989.47 baht. This result suggests that households with

Table 4.13 The Fixed Effect Model with PSM Estimations for VF Borrowers' Income and Expenditure

Variables	Income	Expenditure				
		Housing	Food	Medical	Educational	Transport
Impact Estimator						
VFs	-1.109	0.006	-0.714	0.982	0.585***	-0.107
Household Head Characteristic						
Female (yes=1)	0.678	0.323***	0.945	2.006**	-	-
Age (years)	-	-	-	-	-0.007	4.469×10^{-04}
Education (years)	0.445***	-0.003	0.031	0.143	-0.028	0.148***
Demographic						
Household Size (persons)	3.793***	0.160**	0.847**	-0.401	0.214**	0.865***
Dependency Ratio	-9.238***	-0.489***	-3.864***	2.085*	0.255	-0.838**
Occupation						
Farmer (yes=1)	-4.390***	0.192*	-0.069	-	0.507**	-0.094
Entrepreneur (yes=1)	-4.950***	0.186	0.548	0.397	0.706***	0.444
Formal Worker (yes=1)	3.463***	0.244*	1.709**	-	-0.005	0.025
Informal Worker (yes=1)	3.69**	-0.053	0.847	0.665	-1.371***	-0.210
Assets						
Assets	-0.003***	$9.99 \times 10^{-04**}$	4.177×10^{-04}	3.287×10^{-04}	-9.62×10^{-05}	$-2.612 \times 10^{-04**}$
Other Variables						
Year 2017 (yes=1)	-1.005	-0.137**	-0.067	1.285***	0.570***	-0.533***
Constant	-2.348	0.016	2.298	-1.397	-0.612	-1.891**
Number of Observations	3,279	3,279	3,279	3,279	3,279	3,279

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

a high dependency ratio have fewer family members working to generate income. Moreover, financial services providers believe that these households will not be able to repay their loans (Wachira & Kihui, 2012; Fongthong & Suriya, 2014).

The SGPs' impact on household income is positive and significant at the 5% level. The result also reveals that SGPs borrowers have a 5854.65 baht higher monthly income than non-borrowers. This result indicates that SGP participation increases borrowers' income. This result is similar to that in Islam's (2011) study that estimated the impact of microcredit programmes on income in Bangladesh. Islam finds that there is a positive, significant impact on self-employment income. This finding suggests that microfinance programmes improve borrowers' welfare. Moreover, increased income is

the result of microfinance investment in working capital (such as seeds, raw materials and fertilizers) and assets (machinery and cash saving). Capital and asset accumulation improve borrowers' income-generation abilities (Armendariz de Aghion & Morduch, 2005; Islam, 2007; Phan, 2012).

SGP Impact on Housing Expenditure

The third column in Table 4.14 shows that education is positive and significant at the 10% level. This result reveals that household heads with higher education levels spend 157.72 baht per month more on housing than those with lower education levels. However, the coefficients of farmer and formal worker are negative and significant at 1% and 5% levels, respectively. This shows that farmers and formal workers spent 2,546.14 and 1,195.95 baht per month, respectively, less on housing than those with other occupations.

The SGP impact on housing expenditure is positive but not significant. Microfinance loans are often used for minor house repairs. Therefore, the impact is not significant (Cintina & Love, 2014). In addition, expenditure related to house repairs is sizable but infrequent, meaning that such expenses are not significant (Kaboski & Townsend, 2012). Moreover, poor borrowers are risk-averse and have limited investment channels, thus they have limited opportunities to take advantage of such loans (Chandoewit & Ashakul, 2008).

SGP Impact on Food Expenditure

The fourth column in Table 4.14 indicates that the female variable is positive and significant at the 5% level. This indicates that households with female household heads are more likely to spend 2,237.75 baht per month more on food. However, the dependency ratio, farmer, and formal worker coefficients are negative and significant at 5%, 5%, and 10% levels, respectively. These results indicate that households with a higher dependency ratio, farmers, and formal workers are less likely to spend more on food. The results also show that a higher dependency ratio, farmers, and formal workers have lower food expenditure by 4,893.69 baht, 2,505.39 baht, and 2,326.50 baht, respectively, per month than lower dependency ratio households and other occupations.

The SGP impact on food expenditure is not significant. Most microfinance loans are short-term loans; the impact of microcredit on food expenditure is not significant (Crépon et al., 2015). In addition, microfinance borrowers may obtain loans as substitutes for informal loans (Banerjee et al., 2015). Banerjee et al. (2015) state that borrowers obtain lower interest loans from microfinance programmes to repay informal loans with higher interest rates. Those authors find no significant difference in consumption patterns.

SGP Impact on Medical Expenditure

Column 5, Table 4.14, shows that the age of the household head variable is positive and significant at the 5% level. This indicates that older household heads are likely to spend 55.34 baht per month more on medical expenses. The number of cars variable is negative and significant at the 5% level, which indicates that households with more than one car are likely to spend 359.09 baht per month less on medical expenses.

The SGP impact on medical expenditure is not significant. This result is similar to Coleman's (2006) study. Coleman evaluated microfinance in northeast Thailand and finds that the impact of microcredit on health expenditure is insignificant. Similarly, Banerjee et al. (2015) find that the impact of Indian microcredit programmes on health expenditure is not significant. Banerjee et al. explain that borrowers obtain loans to invest in their businesses but their profits are not enough to improve their livelihood. The loans are short-term and therefore cannot improve welfare.

SGP Impact on Education Expenditure

The sixth column in Table 4.14 indicates that the year 2017, farmer and formal worker variables are positive and significant at 5%, 10%, and 10% levels, respectively. These results suggest that 2017, farmers and formal workers spend 1,517.36 baht, 2,164.65 baht and 1,912.68 baht, respectively, more per month on education than other households. However, the informal worker variable is negative and significant at the 1% level. Informal worker households are likely to spend 8,385.10 baht per month less on education than other households.

The SGP impact on education expenditure is not significant. Banerjee et al. (2015) state that most microfinance participants borrow money for business and investment. Tarozzi, Desai, and Johnson (2015) find that there is no significant impact on education expenditure in Ethiopia. Moreover, they note that the increased school attendance rates for children aged between 6 and 15 years is very small and insignificant. Tarozzi et al. (2015) explain that access to credit increases the demand for child labour. They also find that increased borrowing from microfinance programmes is associated with decreased school attendance rates because teenagers are sent to work in the fields.

SGP Impact on Transport Expenditure

The seventh column in Table 4.14 shows that the education variable is positive and significant at the 5% level. This result suggests that household heads with higher education levels spend 246.67 baht per month more on transport. Assets are negative and significant at the 1% level. This suggests that households with more assets are likely to spend 1.41 baht per month less on transport.

The impact estimator on household transport expenditure is significant at the 10% level. This shows that SGP borrowers have higher transport expenses by 1,237.44 baht per month than non-

borrowers. This result indicates that SGP loans help borrowers increase their transport expenditure. Higher transport expenditure implies that households conduct more business (Awan & Juiya, 2015). Vehicles are necessary production inputs and provide a means of travel to work (Kaboski & Townsend, 2012). Kaboski and Townsend (2012) note that vehicle repairs are an investment that has high returns. Hickson et al. (2013) state that Thai farm households need a vehicle to travel to their farm and to transport their products to markets. Lower-income households also use vehicles to complete jobs in different places. Karlan and Zinman's (2010) investigation into the impact of commercial credit on transport expenditure in South Africa finds that the most common reason for borrowing is to cover transport expenses.

Table 4.14 The Fixed Effect Model with PSM Estimations for SGP Borrowers' Income and Expenditure

Variables	Income	Expenditure				
		Housing	Food	Medical	Educational	Transport
Impact Estimator						
SGPs	5.855**	0.754	0.909	0.009	0.390	1.237*
Household Head Characteristic						
Female (yes=1)	-	-	2.238**	-0.217	0.406	-
Age (years)	0.153	-0.018	0.025	0.055**	0.029	0.019
Education (years)	0.896**	0.158*	0.206	-	-	0.247**
Married (yes=1)	-	-	-	-	1.40	-
Single (yes=1)	-	-	2.291	-	-	-
Demographic						
Household Size (persons)	3.145**	-	-	-	-	0.411
Dependency Ratio	-20.989***	-	-4.894**	-	-	-1.39
Occupation						
Farmer (yes=1)	-8.611**	-2.546***	-2.505**	-	2.165*	0.216
Entrepreneur (yes=1)	-13.547***	-1.191	-0.971	-	1.495	-0.929
Formal Worker (yes=1)	-2.157	-1.196**	-2.327*	-	1.913*	0.592
Informal Worker (yes=1)	-3.111	-1.415	-2.750	-	-8.385***	0.357
Assets						
Assets	0.002	-	-	-	-	-1.413 × 10 ⁻⁰³ ***
Number of Cars	-	-	-	-0.359**	-	-
Other Variables						
Year 2017 (yes=1)	3.442	-0.528	0.324	0.075	1.517**	-0.797
Constant	-1.869	2.550**	6.139**	0.042	-3.61	-0.139
Number of Observations	514	519	519	514	519	514

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.
Source: Author's calculations

The results show that SGP affects only income and transport expenses. This indicates that SGPs do not help borrowers improve their housing or encourage borrowers to spend more on education, food or healthcare. However, the result suggest that SGP loans can improve income and encourage borrowers to increase investment in working capital and assets. This ultimately improves borrowers' income-generating ability (Armendariz de Aghion & Morduch, 2005; Islam, 2007; Phan, 2012).

4.4 Chapter Summary

This chapter discusses the empirical results of the credit participation and welfare impact models. The empirical results from the multinomial logit model reveal that VFs target low-income households in rural areas. VFs also encourage older, less educated and female household heads to participate in their programme. Larger households are more likely to access VFs. Households with higher dependency ratios are less likely to borrow from VFs. This suggests that VFs cannot help less economically active households. Farmers, entrepreneurs, formal and informal workers are the VFs' primary borrowers. Significantly, VF borrowers do not have problems accessing other loans, like emergency loans.

For SGPs, well-educated, young household heads in regional areas are more likely to borrow money from SGPs. SGPs' borrowers have higher household incomes than those who borrow from VFs. These borrowers can also access other loans, such as emergency loans. Larger households are more likely to participate in SGPs. Entrepreneurs are the primary SGP borrowers.

Less-educated and female household heads in rural areas are more likely to borrow from both VFs and SGPs. Like the two previous groups, these borrowers can access other loans, such as emergency loans. Larger households have a higher probability of borrowing from both programmes. VFs' and SGPs' main borrowers are farmers, entrepreneurs, formal and informal workers.

The PSM models estimate the welfare impacts of VF and SGP participation on income and expenditure. Participation in a VF has a significant impact on income, education, and transport expenditure but not on housing, food, or medical expenditure. However, the sign of these variables is negative. This result indicates that VFs do not improve borrowers' wellbeing. VF borrowers spend their loans on non-consumption expenditure; VF borrowers do not spend loans on investment activities (Chandoevrit & Ashakul, 2008). In addition, VF loans are not large enough to improve income and expenditure (Chandoevrit & Ashakul, 2008). For SGPs, the results reveal that SGP effects are significant in terms of income but not in terms of expenditure. This result indicates that SGP borrowers effectively invest their loans in income-generating activities, such as agricultural production and self-employment.

PSM is a useful method for controlling bias due to observed determinants in impact evaluation; however, PSM cannot control for unobserved characteristics. Panel data can control for unobserved bias. This study uses the fixed effect model with PSM to evaluate the VF and SGP impact on household income and expenditure. The results show that participation in the VF impacts only on educational expenditure; in other words, borrowers spend more money on education. Thai farmers in rural areas have limited money during the planting season. If they have any expenses, like their children's school fees, they must borrow money to pay these bills. Our results suggest that the VF helps them meet this need (Yostrakul, 2018).

The fixed effect model with PSM also shows that SGPs affect income and transport expenditure. This indicates that SGPs can improve borrowers' income and encourage borrowers to increase investment in working capital and assets. SGPs' borrowers spend more on transport expenditure; vehicles are necessary production inputs (Kaboski & Townsend, 2012). Cars and motorcycles can help households transport products from remote areas to their shops and markets (Awan & Juiya, 2015). Vehicle ownership is essential for Thai households, especially middle-income farmers. Farmers need vehicles to travel to their farms and transport crops to the market. Labourers need to have vehicles because they work in several locations (Hickson et al., 2013). Higher transport expenditure indicates that households conduct more business (Awan & Juiya, 2015; Hickson et al., 2013). The next chapter discusses the performance of VFs and SGPs and investigates the factors that affect MFI sustainability.

Chapter 5

MFIs' Performance and Sustainability

Chapter 5 discusses Thai MFIs' performance and sustainability. Section 5.1 describes the performance of the MFIs under investigation. Section 5.2 discusses factors that influence MFIs' sustainability. Finally, section 5.3 summarizes the findings.

5.1 Performance of MFIs in Thailand

This section investigates MFIs' performance. This includes the study methodology and data, VF and SGP characteristics, outreach, productivity, differences between VF and SGP financial structures, and financial performance.

5.1.1 Methodology and Data

This study analyses and compares VFs' and SGPs' performance based on MFIs' characteristics, outreach, productivity, financial structure and financial performance. MFIs' characteristics include age, personnel, profit, total assets, total liability, and total equity. Outreach consists of the total number of members, the total number of borrowers and the average loan balance per borrower. Productivity consists of borrowers per staff member and loans per staff member. Financial structure covers capital to asset ratio, debt per equity, deposit per loan, and gross loan portfolio per asset. In terms of financial performance, this study uses three financial ratios: ROA, ROE, and OSS.

To evaluate MFIs' performance, this study uses data collected from annual VF and SGP reports from 2014 to 2016. This study uses data for the period of 2014-2016 because the GSB only has information for this period. The Thai government does not have a database that contains the most recent data. There are 90 VFs and 70 SGPs in Thailand. Annual reports were collected by the GSB. The GSB collected this data through the 2017 MFI competition. The MFI contest is an annual event run by the GSB. Over 100 MFIs across Thailand participated in the contest. The contest objectives are, first, to encourage communities to develop MFIs and secondly, to raise community awareness of local MFI management teams. The target groups for this contest are: (1). community financial institutions, (2) VFs, and (3) SGPs. The MFI contest judges and ranks competitors in terms of three features: (1). financial management, (2) good management practices, and (3) the benefits for members, society and the community. This study also uses descriptive statistics to assess VFs' and SGPs' performance.

5.1.2 VF and SGP Characteristics, Outreach and Productivity

This section compares the VF and SGP characteristics outreach and productivity. Table 5.1 shows that VFs and SGPs have an average age of 13.09 and 10.61 years, respectively. The means the groups are significantly different at the 1% level. Age refers to the total years that an MFI has been in operation (Woldeyes, 2012). Kar (2012) states that older MFIs may benefit from organizational learning.

Organizational learning is learning within a specific organization that involves the interaction of multiple levels of analysis (individual, group, organizational and inter-organizational). The process includes creating, retaining, and transferring knowledge within an organization. An organization improves over time as it gains experience. From this experience, an organization can create knowledge (Argote & Miron-Spektor, 2011; Popova-Nowak & Cseh, 2015). Learning considers productivity and efficiency and how these can be improved (Kar, 2012). Cull et al. (2007) evaluated the financial performance and outreach of 124 MFIs in 49 developing countries. The authors find a positive relationship between MFI age and sustainability. Robinson (2001) explains that experienced MFIs, or those over six years old, are 102% financially self-sufficient. Those between three and six years old are 86% financially self-sufficient, whereas those that have been in operation for less than three years are only 69% financially self-sufficient. This implies that an MFI's age affects its financial sustainability. Our results for the average age of VFs and SGPs indicate that both types of MFI would benefit from organizational learning.

Table 5.1 shows that SGPs have a higher average number of members and borrowers than VFs. The average numbers of SGP members and borrowers are 445.54 and 106.72, respectively; VFs have an average of 347.38 members and 97.04 borrowers. The number of members for the MFI types are significantly different at the 5% level. The average SGP loan amount per borrower is significantly higher at the 5% level than for VFs. The average loan for SGPs and VFs is 32,377.61 and 27,008.03 baht per borrower, respectively. The average loan balance per borrower is measured using depth of outreach (Ledgerwood, 1998). Smaller loans reflect a poorer client base (Cull et al., 2007; Mersland & Storm, 2009). Table 5.1 indicates that VFs provide more loans to poorer clients than SGPs.

The average number of staff members per VF and SGP is 10.68 and 11.26 persons, respectively. The number of staff members is significantly different at the 10% level. VFs and SGPs have similar numbers of borrowers per staff member (9.08 and 8.77) (see Table 5.1). A higher ratio reflects an MFI's ability to use its staff members efficiently. Our finding indicates that the efficiency of staff member use for both MFIs does not differ in terms of monitoring borrowers. However, for SGPs, loans per staff member are significantly higher at the 1% level than for VFs. Total loan amounts per staff member for SGPs and VFs are 288,952.6 and 194,390.7 baht, respectively. The loans per staff member ratio is used to measure staff productivity in terms of loan management. Table 5.1 results

suggest that SGP staff members are more productive than VF staff members. In addition, SGP profits, 118,253.6 baht per year, are significantly higher at the 1% level than VF profits.

Table 5.1 Institutional Characteristics, Outreach and Productivity of Thai VFs and SGPs (average values from 2014 to 2016)

Element	Benchmark		T-test
	VFs	SGPs	P-value
Institutional Characteristic			
Age (years)	13.09	10.61	0.000***
Personnel (Persons)	10.68	11.26	0.0334**
Profit (Baht)	112623.10	230867.60	0.0000***
Total Assets (Baht)	2576263.00	5513542.00	0.0000***
Total Liability (Baht)	78813.04	2861209.00	0.0000***
Total Equity (Baht)	2499516.00	2693207.00	0.4833
Outreach			
The Number of Members (Persons)	347.38	445.54	0.0117**
The Number of Borrowers (Persons)	97.04	106.72	0.2950
Average Loan Balance per Borrower (Baht per Borrower)	27008.03	32377.61	0.0262**
Productivity			
Borrowers per Staff Member	9.08	8.77	0.7308
Loan per Staff Member	194390.70	288952.60	0.0075***

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.
Source: Author's calculations

SGPs' total assets are significantly higher at the 1% level, almost double those of VFs (5,513,542 baht and 2,576,263 baht, respectively). The MFI assets reflect the MFI size. Larger MFIs can benefit from economies of scale by reducing operating expenses and therefore achieving greater financial performance (Meyer, 2019). Our results imply that SGPs gain more benefit from economies of scale than VFs. In addition, larger MFIs can reach more people than smaller MFIs (Mersland & Storm, 2009). This implies that SGPs can reach greater number of borrowers than VFs.

SGPs have significantly higher (at the 1% level) liabilities than VFs, approximately 36 times (2,861,209 baht and 78,813.04 baht, respectively). Total liabilities include all deposits, debts, accounts payable, and other liability accounts (CGAP, 2003). When MFIs take on more debt instruments, efficient liability management and planning are key to growing the institutions (Bayai & Ikhide, 2016). SGPs were established by community leaders or citizen groups to promote savings among members, to provide credit to improve members' lives, and to make emergency funds available (Meagher, 2013). In short, SGPs are funded through member deposits. The results suggest that if SGPs manage and plan their liabilities efficiently, SGPs can grow more than VFs. However, long-term debts are relatively more expensive and, therefore, employing a high proportion of such debts could lead to lower profitability (Kar, 2012). SGPs should be concerned about the cost of such liability.

SGPs' and VFs' total equity are similar. The total equities are 2,693,207 and 2,499,516 baht, respectively (see Table 5.1). Total equity is the sum of all equity accounts net of any equity distributions; e.g., dividends, stock repurchases, or other cash payments made to shareholders (CGAP, 2003). Equity has an impact on MFI performance because equity is cheap, leading to higher FSS (Bayai & Ikhida, 2016; Kar, 2012). Nyamsogoro (2010) states that equity is a relatively cheap source of funding; equity can improve MFI sustainability. Some Thai MFIs' equity comes from the government. The programmes do not have an objective to make a profit from poor people. This makes equity a relatively cheap source of finance and, thus, improves MFIs' financial sustainability.

5.1.3 VF and SGP Financial Structures

This section compares VFs' and SGPs' financial structures using the capital per asset, debt per equity, deposit per loan, and gross loan portfolio per asset ratios. The VF capital per asset ratio is significantly higher at the 1% level than the SGPs'. Both the VFs' and SGPs' capital per asset ratios are far above that of the Global and FSS benchmarks (see Table 5.2). The capital per asset ratio is used to evaluate MFIs' solvency. This ratio also shows an MFI's ability to meet its obligations and absorb unexpected losses (Yenesew, 2014). Yenesew (2014) states that the determination of an acceptable ratio level is generally based on an MFI's assessment measures, which include expected losses, financial strength, and the ability to absorb losses. This ratio measures the amount of capital required to cover unexpected losses. Our study uses the capital per asset ratio as a proxy for MFI capital. This means that if an MFI has a higher capital per asset ratio, it is safer than lower ratio institutions. Therefore, both VFs and SGPs are relatively safe compared with Global and FSS benchmarks.

Table 5.2 A Comparison of Thai MFIs' Financial Structures (average values from 2014 to 2016)

Indicator	Financial Structure		T-test	Benchmark ¹	
	VFs	SGPs	P-value	Global	FSS
Capital per Asset Ratio	0.98	0.68	0.0000***	0.2398	0.231
Debt per Equity	0.08	3.23	0.0000***	0.0286	0.033
Deposits per Loan	0.01	0.40	0.0000***	0.1107	0.118
Deposits per Total Assets	0.00	0.19	0.0000***	0.0597	0.089
Gross Loan Portfolio per Assets	0.77	0.64	0.0193**	0.7685	0.784

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

¹Benchmark refers to the 2009 Global and Financial Self Sufficiency (FSS) ratio of MFIs (Shaoyan & Duwal, 2012).

Source: Author's calculations

The SGP average debt per equity ratio is above the VF average ratio and significantly different at the 1% level. Both the VF and SGP average ratios are higher than Global and FSS benchmarks - especially the SGP ratio (see Table 5.2). These results indicate that SGPs are savings-based organizations (the SGP ratio is much higher than the VF ratio). This also implies that SGPs have greater creditor risks.

However, Muriu (2011) concludes that if MFIs employ more debt in their capital structure, these institutions can increase their profit. Our finding shows that SGP profits are significantly higher at the 1% level than VF profits, 118,253.60 baht per year.

There is a significant difference at the 1% level in the deposit to loan ratio for VFs and SGPs. Though the VF deposit per loan ratio is lower than the Global and FSS benchmarks, the SGP ratio is much higher (see Table 5.2). Eur-U-Sa (2011) evaluated the performance of the BAAC in Thailand. The author finds that the BAAC deposit per loan ratio gradually increased between 1967 and 2009. This suggests that the BAAC is moving towards becoming a self-financing institution. Muriu (2011) explains that external funding is more costly than deposits, thus MFIs may effectively use local depositors. This study's finding indicates that deposits are SGPs' main source of funding.

The VF and SGP gross loan portfolio per asset ratios differ significantly at the 5% level but they are similar to the Global and FSS benchmarks (see Table 5.2). Rahman and Mazlan (2014) used this ratio to compare five Bangladeshi MFIs' financial structures. Their results show that Bangladesh MFI gross loan portfolio to assets ratio is high. Bhuiyan et al. (2011) used this ratio to compare the financial structure of MFIs in Malaysia and Bangladesh. Their results reveal that MFIs in Malaysia have higher gross loan portfolio to assets ratio than MFIs in Bangladesh. The gross loan portfolio per assets ratio is a key indicator of financial structure. This ratio indicates an MFI's proportion of core earning assets. Rahman and Mazlan's (2014) and Bhuiyan et al.'s (2011) results reveal that Malaysia and Bangladesh MFIs' core earning assets are loans. Mahapatra and Dutta (2016) state that the gross loan portfolio acts as an indicator of an MFI's main source of income. In short, the bigger the loan, the more interest income they will make. Our results indicate that both VFs' and SGPs' core earning assets are loans.

5.1.4 VF and SPG Financial Performance

This section evaluates the financial performance of VFs and SGPs using ROA, ROE, and OSS. Table 5.3 compares the average financial performance of VFs and SGPs between 2014 and 2016. The results show that there is a significant difference at the 1% level between the ROAs for VFs and SGPs. For both VFs and SGPs, the ROA ratio is higher than Global and FSS benchmarks. This result indicates that both VFs and SGPs can deploy their assets profitably. As Ngo (2012) notes, ROA is used to measure profitability in commercial institutions. Rahman and Mazlan (2014) used ROA to compare the financial performance of five MFIs in Bangladesh. They conclude that Bangladesh MFIs are financially sustainable because the ROA ratio is positive. Agarwal and Sinha (2010) used ROA to evaluate the financial performance of Indian MFIs. The authors find that MFIs in India are also financially sustainable. Wassie, Kusakari, and Sumimoto (2019), who evaluated Ethiopian MFIs performance using ROA, find that they also perform well.

In terms of ROE, the SGP ratio is significantly higher at the 1% level than the VF ratio. Though the SGPs' average ROE is above the Global and FSS benchmarks, the VFs' average ROE is lower than both benchmarks (see Table 5.3). The lower VFs' average ROE is not surprising given that its equity comes from the government; they do not prioritize profits because their core objective is to assist the poor. VFs play an important role in the Thai credit market, especially for poor individuals who live in rural areas and cannot access formal financial services (Fongthong & Suriya, 2014). The ROE ratio is important only for profit-earning institutions (Shaoyan & Duwal, 2012). Ngo (2012) notes that the ROE ratio tends to encourage investors to reinvest in MFIs. Likewise, Ledgerwood (1998) states that this ratio is a crucial indicator for private investors when deciding whether to invest in MFIs. This ratio is the most common indicator used to assess financial sustainability. Table 5.3 shows that the average ROEs for VFs and SGPs are positive, indicating that both are financially sustainable.

Table 5.3 shows that the OSS of VFs is significantly at the 1% level above that of SGPs. The OSS of both VFs and SGPs is higher than the Global and FSS benchmarks. OSS measures operating income and includes operating costs, such as salaries and wages, supplies, loan losses, and other administrative costs (Meyer 2002). Ngo (2012) states that OSS is one indicator used to assess the financial sustainability of MFIs. Rahman and Mazlan (2014) compared the financial performance of five MFIs in Bangladesh using the OSS. They find that all MFIs are financially sustainable. Bhuiyan et al. (2011) compared the financial sustainability of Malaysian and Bangladeshi MFIs using OSS. Their results show that Malaysian MFIs perform better than the Bangladeshi MFIs in terms of the OSS. Our results indicate that both types of MFI are profitable and financially sustainable.

Table 5.3 A Comparison of Thai MFIs' Financial Performance (average values from 2014 to 2016)

Indicator	Financial Performance		T-test	Benchmark ¹	
	VFs	SGPs	P-value	Global	FSS
Return on Assets	0.05	0.07	0.0000***	0.01	0.02
Return on Equity	0.06	0.31	0.0000***	0.07	0.11
Operational Self-Sufficiency	13.59	2.94	0.0011***	1.09	1.17

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

¹Benchmark refers to the 2009 Global and Financial Self Sufficiency (FSS) ratio of MFIs (Shaoyan & Duwal, 2012).

Source: Author's calculations

In summary, this section investigated VFs' and SGPs' performance, comparing their financial structures and performance. The results indicate that SGPs perform better than VFs in terms of the number of members, loans per staff member and profit. The results show that SGPs have an average of 445.54 members and VFs have an average of 347.38 members. These averages differ significantly at the 5% level. The SGPs' loans per staff member ratio is significantly higher at the 1% level than the VFs one. The loans per staff member ratio is used to measure productivity. In short, SGP staff members are more productive in terms of loan management than VF staff. SGPs' average profit is

significantly higher at the 1% level than VFs', by 118,253.6 baht per year,. SGPs have greater assets and liabilities than VFs. However, VFs and SGPs are similar in terms of the number of borrowers, borrowers per staff member and total equity. SGPs' funds come from members' savings (Meagher, 2013). In contrast, VFs were established by the Thai government with one million baht given to each VF (Fongthong & Suriya, 2014), i.e., SGPs are funded through member deposits but VFs are subsidized by the government. This study concludes that SGPs perform better than VFs in terms of the number of members, loans per staff member and profit. Muriu (2011) finds that higher deposits, as a percentage of total assets, are associated with improved profitability. In addition, deposit funding can help MFIs achieve independence from investors and donors because deposit funding provides MFIs with an inexpensive, sustainable source of loan funds (Muriu, 2011).

Regarding the financial structure, the VF capital per asset ratio is significantly higher at the 1% level than SGPs. Both VFs' and SGPs' capital per asset ratios are above the Global and FSS benchmarks. This suggests that both VFs and SGPs are relatively safe from financial risk. MFIs with higher capital per asset ratios are considered relatively safe compared with MFIs with lower ratios (Yenesew, 204). The capital per asset ratio is used to evaluate MFI solvency. This ratio shows an MFI's ability to meet its obligations and absorb unexpected losses (Yenesew, 2014). This study uses the capital per asset ratio as a proxy for MFI capital. This means that if an MFI has a higher capital per asset ratio, it is regarded as safer than an institution with a lower ratio. The SGP debt per equity ratio is above that of the VFs. Both MFIs' ratios are higher than the Global and FSS benchmarks - especially the SGP ratio. This result shows that SGPs are savings-based organizations, as indicated by their deposits per loan and deposits per total asset ratios, 0.40 and 0.19, respectively. Eur-U-Sa (2011) states that if a bank's deposits per loan ratio is higher, then it is moving towards becoming a self-financing institution. Muriu (2011) explains that external funding is more costly than deposits, thus MFIs may effectively use local deposits. This finding indicates that SGPs depend more on deposits, their main source of funding.

The gross loan portfolio per assets ratio indicates that both VFs' and SGPs' core earning assets are loans. The gross loan portfolio per assets is a financial structure indicator. This ratio reveals the proportion of an MFI's core earning assets. Mahapatra and Dutta (2016) state that the gross loan portfolio is the main source of an MFI's income. In short, if an individual MFI has a higher loan ratio, its income from interest will be higher. Our result indicates that both VFs' and SGPs' core earning assets are loans. Our study suggests that if VFs and SGPs grant more loans, they will increase their revenue from interest and, eventually, their profit. In terms of financial performance, both VFs and SGPs are profitable and financially sustainable. Our results indicate that the VFs' operational self-sufficiency is significantly higher at the 1% level than SGPs. Both VFs' and SGPs' operational self-sufficiency ratios are higher than the Global and FSS benchmarks. Our results indicate that VFs and

SGPs can cover all their costs and that these institutions are financially sustainable. The next section investigates the factors affecting MFIs' sustainability.

5.2 The Sustainability of Thai MFIs

5.2.1 Data and Methodology

To evaluate the MFIs' sustainability, this study uses data collected from the annual reports of both VFs and SGPs from 2014 to 2016. These annual reports were collected by the GSB via the MFIs competition in Thailand in 2017. There are 90 VFs and 70 SGPs across the country.

A panel regression model is used to identify the determinants of MFI financial self-sufficiency. I use the panel regression model because of its advantages over cross-section and time-series data methods (Kinde, 2012). Panel data involves the pooling of observations on a cross-section of units over several time periods (Kinde, 2012). This method can increase the degrees of freedom and, therefore, the power of the test (Kinde, 2012). In short, panel data are more useful than either cross-section or time-series data alone.

Before using the regression model, I test it for normality. I test the distribution of the variables using a plot of each variable. From the visual plot, it is evident that the distribution of some variables is not normal; some variables (the financial self-sufficiency ratio; total assets; the personnel productivity ratio; the average loan balance per borrower; and the ratio of operating expenses) are skewed. The test also shows evidence of normal distribution for the debt to equity ratio. Non-normally distributed variables can distort relationships and significance tests (Osborne & Waters, 2002). To solve this non-normal distribution problem, this study uses variable transformation as suggested by Cameron and Trivedi (2009), Verbeek (2008) and Wooldridge (2009). This study transforms the variables to their natural log. The log transformed variables can help to attain linearity in a parameter that is a requirement for regression analysis (Nyamsogoro, 2010). The panel regression model for MFI financial self-sufficiency (Kinde, 2012) is:

$$LN(FSS_{it}) = \alpha_i + \beta_1 LN(YIE_{it}) + \beta_2 LN(SIZ_{it}) + \beta_3 LN(PP_{it}) + \beta_4 DE_{it} + \beta_5 LN(ALBPB_{it}) + \beta_6 LN(OER_{it}) + \epsilon_{it} \quad (5.1)$$

Where:

$LN(FSS_{it})$: is the natural log of the financial self-sufficiency ratio of MFI i at time t ;

α_i : is a constant;

$LN(YIE_{it})$: is the natural log of yield on gross loan portfolio of MFI i at time t ;

$LN(SIZ_{it})$: is the natural log of total assets of MFI i at time t ;

$LN(PP_{it})$: is the natural log of personnel productivity ratio of MFI i at time t ;

DE_{it} : is the debt to equity ratio of MFI i at time t ;

$LN(ALBPB_{it})$: is the natural log of average loan balance per borrower of MFI i at time t ;

$LN(OER_{it})$: is the natural log of the ratio of operating expense of MFI i at time t ; and

ϵ : is the error term.

This model (Equation 5.1) estimates the impact of each explanatory variable on the financial self-sufficiency ratio. The impact of each variable is assessed in terms of the statistical significance of the coefficients. These coefficients are derived using the panel regression model, which may be subject to omitted variables bias. This situation occurs when some variables not included in the model affect the dependent variable. If a researcher does not control for these variables, the coefficients' estimation will lead to an omitted variables bias (Kinde 2012; Wooldridge, 2009). Controlling for the omitted variables bias depends on the nature of the omitted variables. Omitted variables bias can be divided into constant or changing over time or constant or changing over cases. These are known as time specific and individual specific effects of unobservable or omitted variables (Kinde 2012). Hsiao (2007) notes that there are two common methods to deal with omitted variables: the fixed effect model and the random effect model.

To choose between a fixed effect model and a random effect model, this study uses the Hausman test that compares the coefficients of the fixed and random effect estimators. This test reveals that the random effect is consistent under the null hypothesis. Table 5.4 shows the random effect model provides more consistent estimates than the fixed effect model. The test results show that the Hausman test statistic is not significant and, therefore, the null hypothesis cannot be rejected. In short, the random effect model provides a more consistent result.

Table 5.4 The Results of the Hausman Fixed Effect and Random Effect Coefficients Test

Variables	Coefficients with Fixed Effects Model (1)	Coefficients with Random Effects Model (2)	Difference, (1) -(2)	SE
LN (Average Loan Balance per Borrower)	0.576	0.473	0.102	0.053
LN (Number of Borrowers per Staff Member)	0.437	0.404	0.032	0.221
LN (Total Assets)	-0.468	-0.360	-0.108	0.062
Debt to Equity Ratio	-0.004	-0.006	0.002	0.002
LN (Operating Expense Ratio)	-0.821	-0.840	0.020	0.025
LN (Yield on Gross Loan Portfolio)	0.826	0.810	0.016	0.021

Note: $\chi^2 = 5.03$; Probability > $\chi^2 = 0.5397$

Source: Author's calculations

This study also investigates the appropriateness of using the random effect model as opposed to pooled OLS using the Breusch and Pagan multiplier test (LM test). The null hypothesis in the LM test is that the variances across the entities equal zero. Table 5.5 shows the results of the LM test. The LM test is statistically significant, which indicates the existence of random effects. The results suggest that pooled OLS regression is not appropriate. Thus, this study uses the random effect model.

Table 5.5 The Results of the Breusch-Pagan Lagrange Multiplier Test (LM Test)

Variables	Var	Sqrt (Var)
LN (Financial Self-sufficiency Ratio)	1.230	1.109
<i>e</i>	0.019	0.139
<i>u</i>	0.138	0.372

Note: Test: $\text{Var}(u) = 0$; $\text{chibar2}(01) = 44.34$; Prob > $\text{chibar2} = 0.0000$

Source: Author's calculations

This study checks for serial correlation in the error term using the Wooldridge test that looks for autocorrelation in the panel data. The null hypothesis is that there is no first-order autocorrelation. The p-value of the test statistic for equation (5.1) is statistically significant. Therefore, we reject the null hypothesis because the test statistic indicates the presence of serial correlation.

This study tests for heteroskedasticity across the explanatory variables using the Breusch-Pagan test. The null hypothesis is that there is no heteroskedasticity. The p-value of the test statistic for equation (5.1) is statistically significant. Thus we reject the null hypothesis, which indicates the presence of heteroscedasticity.

The random effect model explains the impact of the determinants of MFI financial sustainability. The model is estimated using heteroskedastic and autocorrelation consistent standard errors, as suggested by Cameron and Trivedi (2009), Verbeek (2008) and Wooldridge (2009). The next section

presents the descriptive statistics of dependent and independent variables of the panel regression model.

5.2.2 Descriptive Statistics

Table 5.6 presents the descriptive statistics of the variables of financial self-sustainability, including the mean, standard deviation, minimum and maximum values of MFIs from 2014 to 2016. The average loan balance per borrower variable shows an MFI's efficiency in selling loans, their primary product (Woldeyes, 2012). Assuming all things are equal, if an MFI sells more loans, it will have greater profitability and operational sustainability. Table 5.6 reveals that the mean average of this variable is 29,254.03 baht, indicating that, on average, MFIs provide 29,254.03 baht to each borrower. The maximum value is 166,666.70 baht and the minimum is 0. The minimum value is zero because some MFIs do not provide loans; they are savings-only institutions.

Table 5.6 The Descriptive Statistics for the Dependent and Independent Variables

Variable	Mean	SD	Minimum	Maximum
Financial Self-sufficiency Ratio	5.41	18.36	0.002	188.03
Yield on Gross Loan Portfolio	0.14	1.08	0	22.7
Total Assets	3,958,338.00	5,391,584.00	11,240.98	39,200,000.00
Debt to Equity Ratio	1.46	6.33	-21.20	64.88
Average Loan Balance per Borrower	29,254.03	22,668.73	0	166,666.70
Operating Expense Ratio	0.02	0.05	0	0.61
Borrowers per Staff Member	8.92	8.29	0	44.44

Source: Author's calculations

In terms of borrowers per staff member, a higher ratio reflects an MFI's ability to use its staff efficiently. Staff productivity is measured by dividing active borrowers by the number of officers (Kinde, 2012). This ratio is called the personnel productivity ratio. Kinde explains that serving a loan client can be more labour intensive and costly than serving a depositor because the process involves a series of interviews and site visits before the loan can be disbursed. Nyamsogoro (2010) studied the relationship between the number of borrowers per staff member and the financial sustainability of Tanzanian MFIs in rural areas. The author concludes that Tanzanian MFIs' staff in rural areas are not efficient because they fail to manage borrowers when the number of borrowers grows. Table 5.6 shows the mean value of borrowers per staff member is 8.92, i.e., one staff member monitors approximately nine customers. The minimum and maximum values are 0 and 45 people (see Table 5.6). The minimum value is 0 because some MFIs do not have any borrowers because they do not provide loans.

Total assets measure if MFIs are large enough to be operationally and financially sustainable (Woldeyes, 2012). Bogan (2012) evaluated how changes in capital structure can improve financial

sustainability through OSS. Bogan's results show that assets and capital structure affect MFI performance. Asset size is positive and significantly influenced by sustainability. Cull et al. (2007) and Woldeyes (2012) find that MFI size significantly, positively affects MFI's FSS. Table 5.6 shows the mean total assets are 3,869,404 baht, with maximum and minimum values of 39,200,000 baht and 11,240.98 baht, respectively. The standard deviation is 5,391,584 baht. The MFIs in our study differ in their asset size.

This study also investigates MFIs' capital structure. The debt to equity ratio indicates an MFI's capital structure. A high debt to equity ratio implies that MFIs are leveraged rather than financed through equity capital (Kinde, 2012). Kinde (2012) investigated the factors affecting the FSS of Ethiopian MFIs. The author finds that the debt to equity ratio has a negative, statistically insignificant impact on FSS. The result implies that a combination of various sources of capital does not improve an MFI's FSS. Nyamsogoro (2010) states that equity is a relatively cheap source of funding; equity can improve MFI sustainability. The author shows that capital structure positively correlates with MFI sustainability. Table 5.6 shows the mean of debt to equity ratio is 1.46. This finding indicates that for every baht owned by the shareholders, Thai MFIs owe 1.46 baht to creditors. This indicates that some Thai MFIs are leveraged rather than financed through equity capital. Interestingly, the minimum value of debt to equity ratio is -21.20 (see Table 5.6). This suggests that some MFIs are incurring losses and that they have more liabilities than assets. However, the maximum value of debt to equity ratio is 64.88 (see Table 5.6) which shows that debt financing is considerably higher than equity capital. This result indicates that some MFIs in Thailand are savings-based organizations and that their MFI debt to equity ratio is much higher. Voluntary deposit mobilization can help MFIs achieve independence from investors and donors because this funding provides MFIs with an inexpensive, sustainable source of loan funds (Muriu, 2011). Muriu (2011) concludes that if MFIs employ more debt in their capital structure, they could increase their profit.

The operating expense ratio refers to total operating costs in relation to outstanding loan portfolios. This variable measures MFI efficiency. Management efficiency enables MFIs to reach more clients and attain higher levels of profitability (Dissanayake, 2012). Nyamsogoro (2010) finds that the operating expense ratio is negatively related to Tanzanian MFIs' sustainability. This means that, if MFIs can reduce their operating costs, they will be more efficient and financially sustainable. Dissanayake (2012) investigated factors affecting MFI profitability in Sri Lanka. The author finds that the operating expense ratio has a negative, statistically significant correlation with MFI sustainability.

Table 5.6 shows that the average operating expense ratio is 0.02. This result indicates that, on average, Thai MFIs absorb two satang in operating expenses for each baht in the gross loan portfolio. Shaoyan and Duwal (2012) explain that the operating expense ratio can be used to compare

administrative and personnel expenses with MFIs' yields on loan portfolios. Shaoyan and Duwal note that if an MFI has a lower operating expense ratio, it is more efficient. Interestingly, some MFIs in Thailand do not have this cost because their staff members are volunteers; they do not earn wages. Table 5.6 shows the minimum value of the operating expense ratio is zero. The VF is administered at two levels (national and the village level) (Meagher, 2013). The national level works with volunteers (VF members from each village). These volunteers deal directly with the funds.

The yield on gross loan portfolio ratio indicates MFI efficiency in terms of generating cash revenue from its outstanding portfolios (Woldeyes, 2012). Yield on gross loan portfolio indicates the efficiency with which an MFI has used its resources to generate cash revenue (Woldeyes, 2012). The greater the ratio, the greater the efficiency. Cull et al. (2007) assessed patterns of profitability, loan repayments, and cost reduction strategies in 124 micro-banks in 49 countries. The authors find that yield on gross loan portfolio is positive and significantly associated with FSS for individual lenders. Woldeyes (2012) concludes that yield on gross loan portfolio indicates an MFI's ability to generate revenue that covers its financial and operating expenses. Table 5.6 shows the mean value for yield on gross loan portfolio is 0.14. This suggests that, on average, these Thai MFIs generate 14 satang for every baht in their outstanding loan portfolios. In this study, the minimum and maximum of this variable are 0 and 22.7, respectively. This result indicates that some MFIs do not generate revenue from loans, whereas more efficient MFIs can generate up to 22.7 baht. As Lewis et al. (2013) note, some savings groups in Thailand are community-run. The objective of these groups is to encourage people to save. Some of these groups also provide their members with welfare services, such as hospital and funeral coverage, education and community development programmes.

The financial self-sustainability variable indicates that an MFI can cover all its operating and capital costs without depending on any subsidy (Kinde, 2012). Kinde (2012) argues that financial sustainability is the key to MFI sustainability. Woldeyes (2012) notes that if the value of financial self-sustainability is below 1, then an MFI has not 'break even' financially. Table 5.6 shows that the mean value of financial self-sustainability is 5.41, which suggests financial self-sustainability. This finding shows that, on average, the financial self-sustainability of the Thai MFIs under consideration is 5.41. This result is above the threshold for sustainability. In short, Thai MFIs are financially self-sustainable.

5.2.3 Empirical Results

The results show that the overall Wald statistic is significant at the 1% level. This rejects the hypothesis that all coefficients are equal to zero. The R-squared values indicate that the proportion of variance in the dependent variable can be explained by the fact that the independent variables are higher within the same MFI than between MFIs (within = 0.9307, between = 0.8856, overall = 0.8912). This indicates high explanatory power within an MFI, i.e., about 93% of the variation in the

dependent variable is explained by the independent variables in the model. In terms of panel data, Cameron and Trivedi (2009) and Hsiao (2007) note that r-squared values above 0.2 are large enough to draw reliable conclusions. These empirical results indicate that six determinants are statistically significant and affect MFI financial sustainability. They are: average loan balance per borrower, the number of borrowers per staff member, MFI size, the debt to equity ratio, the operating expense ratio, and the yield on the gross loan portfolio (see Table 5.7).

There is a positive relationship between the average loan balance per borrower and financial sustainability. The relationship is significant at the 1% level (see Table 5.7). This result is similar to that of Adongo and Stork (2005) who investigated factors influencing the financial sustainability of Namibian MFIs. They find that profitability is related to bigger loans. Nyamsogoro (2010) finds a positive and statistically significant correlation between the average loan balance per borrower

Table 5.7 The Results of the Determinants of Financial Self-sustainability

Variable	Coefficient	Robust SD	P-Value
LN (Average Loan Balance per Borrower)	0.473	0.122	0.000***
LN (Borrowers per Staff Member)	0.404	0.088	0.000***
LN (Total Assets)	-0.360	0.109	0.001***
Debt to Equity Ratio	-0.006	0.003	0.068*
LN (Operating Expense Ratio)	-0.840	0.049	0.000***
LN (Yield on Gross Loan Portfolio)	0.810	0.080	0.000***
Constant	-0.307	0.679	0.652
R-Sq	Within = 0.9307, Between = 0.8856, Overall = 0.8912		

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Author's calculations

and MFI sustainability. The result indicates that MFIs' profitability is associated with greater loan size. This means larger loans are more cost efficient and, therefore, more profitable. The average loan balance per borrower is used as a proxy measure for depth of outreach (Adongo & Stork, 2005; Cull et al., 2007; Nyamsogoro, 2010). Smaller loans indicate poorer borrowers (Adongo & Stork, 2005; Cull et al., 2007; Nyamsogoro, 2010). Our results suggest that Thai MFIs do not lend money to the very poor. Fongthong and Suriya (2014) and Rungruxsirivorn (2011) find that Thai MFIs reach near-poor households and lower-income households (with income above the poverty line), but not the very poor.

The number of borrowers per staff member is a significant positive factor at the 1% level affecting the sustainability of MFIs (see Table 5.7). This result is similar to that in Crombrughe et al. (2008), who evaluated Indian MFIs' performance. They find that an increase in the number of borrowers per staff member increases MFIs' sustainability. Hossain and Khan (2016) who studied Bangladeshi MFIs' sustainability, find that there is a positive relationship between the number of borrowers per staff

member and MFIs' financial sustainability. Hossain and Khan (2016) conclude that if a staff member serves a larger number of borrowers, then an MFI will be more financially sustainable. Nyamsogoro (2010) points out that the number of borrowers per staff member shows an MFI's efficiency. The result implies that Thai MFI staff members are more efficient at managing borrowers when the number increases. This leads to MFI sustainability. Thai MFI committees are normally limited to 15 members. MFIs have a simple committee structure, with a chairperson, a vice-chair, a treasurer, secretary, and staff members (Boonperm et al., 2013; Meagher, 2013). Village residents vote for individual management committee members. A key aim of Thai MFIs is a high level of village participation (Meagher, 2013).

A significant negative relationship at the 1% level between MFI size and MFI sustainability suggests that larger MFIs are less likely to be sustainable (see Table 5.7). Our result is similar to that in Yenesew (2014), who investigated factors affecting Ethiopian MFIs and finds a negative relationship between MFI size and financial performance. Yenesew states that large MFIs do not benefit from economies of scale. Yenesew explains that diseconomies of scale might occur because of the existence of a bureaucratic bottleneck and inefficiency in terms of asset management. Sima (2013), who examined factors affecting Ethiopian MFIs profitability, states that MFIs have become too complex to manage and diseconomies of scale occur when they are too large. The author finds that Ethiopian MFIs do not benefit from economies of scale.

Our finding is contrary to both Cull et al. (2007) and Woldeyes (2012). Cull et al. (2007) and Woldeyes (2012) find that MFI size is significant and positively affects financial sustainability. Cull et al. (2007) conclude that MFI size is significant and positively related to three financial performance indicators: FSS, OSS, and ROA. Woldeyes agrees with Cull et al.'s argument that a change in size causes a positive change in OSS. Cull et al. (2007) and Woldeyes (2012) conclude that size is positive and significantly related to financial performance, reflecting the cost advantages associated with size (economies of scale). This study suggests that larger MFIs are less likely to be sustainable because they do not benefit from economies of scale.

Diseconomies of scale lead to increased unit costs because of MFIs getting too large or expanding too quickly (Ngo, 2012). A lack of efficient MFIs to deliver financial services is a big problem (Meyer, 2002). Meyer (2002) states that there are more funds available from governments and donors than efficient market-oriented MFIs can absorb and efficiently use. Therefore, MFIs should prioritize building and strengthening themselves. Meyer (2002) suggests that the increasing availability of technology and non-proprietary information among MFIs across various networks and associations will help them to improve their efficiency.

The debt to equity ratio is negative and significant at the 10% level (see Table 5.7). A high debt to equity ratio implies that MFIs are leveraged rather than financed through equity capital. The result suggests that a higher debt to equity ratio is less likely to lead to MFI sustainability. Tehulu (2013) investigated the determinants affecting MFI financial sustainability in East Africa. The author uses unbalanced panel data from 23 MFIs between 2004 and 2009 and finds that the debt to equity ratio has a negative and statistically significant impact on FSS. This result implies that a combination of various sources of capital does not improve an MFIs' FSS. The negative relationship between debt to equity and MFI sustainability suggests that the more MFIs are debt-financed (compared with other sources of finance), the less sustainable they are. Tehulu (2013) explains that MFIs, especially those in Ethiopia, do not pay dividends, and this makes equity a relatively cheap source of finance compared with debt financing. According to Nyamsogoro (2010), equity is a relatively cheap source of funding and can improve MFI sustainability. Nyamsogoro's study shows that capital structure is positively correlated with MFI sustainability.

There is a significantly negative relationship at the 1% level between the operating expense ratio and MFI sustainability (see Table 5.7). This result indicates that the higher the operating expense ratio is, the less sustainable an MFI is likely to be. The lower an MFI's operating expense ratio, the more efficient it will be. In short, if the operating expense ratio is low, then the MFI is operating efficiently (Nyamsogoro, 2010). Our finding is similar to Nyamsogoro's (2010), who concludes that the operating expense ratio is negatively related to MFI sustainability. Dissanayake (2012) investigated factors affecting MFI profitability in Sri Lanka. The author finds that the operating expense ratio has a negative, statistically significant correlation with MFIs' sustainability. Dissanayake states that this variable provides an overall measure of MFI efficiency. In short, efficient management practices enable MFIs to reach more clients and attain higher profit.

The yield on gross loan portfolio variable is positive and significant at the 1% level in terms of MFI sustainability (see Table 5.7). This result suggests that an increase in yield on gross loan portfolios increases MFI sustainability in Thailand. The yield on gross loan portfolio indicates an MFI's ability to use short-term assets to generate cash or financial revenue. In short, if an MFI uses more of its short-term assets, it can generate higher revenue, which, in turn, increases its sustainability (Woldeyes, 2012). Woldeyes (2012) states that the yield on gross loan portfolio indicates an MFI's efficiency in generating cash revenue from its outstanding portfolio. Cull et al. (2007) assessed patterns of profitability, loan repayments, and cost reduction strategies in 124 micro-banks in 49 countries. The authors find that yield on gross loan portfolio is positive and significantly associated with FSS for individual-based lenders. Nyamsogoro (2010) evaluated the financial sustainability of MFIs in Tanzania and finds that there is a positive relationship between gross loan portfolio yields and FSS.

This section investigated the determinants affecting MFI sustainability using the panel regression model. The study found six determinants are statistically significant: the number of borrowers per staff member, MFI size, the debt to equity ratio, the operating expense ratio, the yield on gross loan portfolio, and average loan balance per borrower.

5.3 Chapter Summary

This chapter discussed the empirical results of Thai MFI performance and sustainability. The chapter compared VF and SGP performance in terms of characteristics, outreach, productivity, financial structure, and financial performance. In terms of characteristics, VFs and SGPs have an average age of 13.09 and 10.61 years, respectively. It has been argued that both VFs and SGPs could benefit from organizational learning, which can improve MFI productivity and efficiency. In terms of breadth of outreach and depth of outreach, SGPs have a higher average number of members and borrowers than VFs. However, VFs provide more loans to poorer clients than SGPs. The average loan per borrower of SGPs is significantly higher than by VFs. In terms of productivity, both MFIs are similar in terms of monitoring their borrowers. However, for the loans per staff member ratio, SGPs are significantly higher at the 1% level than VFs. This result suggests that, in loan management, SGP staff are more efficient than VF staff. In addition, SGPs' profits are significantly higher than VFs'. Considering total assets, SGPs' assets are significantly higher – twice as much as VFs'. This result indicates that SGPs are larger than VFs. The information indicates that SGPs are funded through member deposits and have significantly higher liabilities than VFs, approximately 36 times. SGPs' funds come from members' savings and VFs are subsidized by the government. This finding is shown by VFs' high equity and low liability.

In terms of financial structure, the VFs' capital per asset ratio is significantly higher at the 1% level than the SGPs' one. Both the VFs' and SGPs' capital per asset ratios are above the Global and FSS benchmarks. Therefore, both VFs and SGPs are relatively safe compared with the Global and FSS benchmarks. Yenesew (2014) states that if an MFI has a higher capital per asset ratio, it is relatively safer than lower ratio institutions. Capital per asset ratio is used to evaluate MFI solvency. This ratio shows an MFI's ability to meet its obligations and absorb unexpected losses (Yenesew, 2014). The debt per equity ratio of SGPs is higher than VFs and significantly different. This result indicates that SGPs are savings-based organizations. The information shows that SGPs have significantly more liabilities than VFs. The VFs' deposit per loans ratio is lower than the Global and FSS benchmarks and the SGPs' ratio is higher than the benchmarks. This finding indicates that SGPs depend more on deposit collection, their primary source of funding; external funding is more costly than deposits. Thus, MFIs may effectively use local deposits (Muriu, 2011). The gross loan portfolio per assets ratio indicates that both VFs and SGPs' core earning assets are loans. The gross loan portfolio per assets

ratio is one indicator of financial structure. This ratio indicates an MFI's proportion of core earning assets. Gross loan portfolio is the MFI's main income source (Mahapatra & Dutta, 2016). MFIs with higher loan values have higher interest income. This analysis of VFs' and SGPs' financial performance indicates that both are profitable and financially sustainable.

This study has identified the determinants that affect MFI sustainability: average loan balance per borrower, borrowers per staff member, size of MFI, debt to equity ratio, the operating expense ratio, and yield on gross loan portfolio. The average loan balance per borrower has a positive and statistically significant impact on MFIs' sustainability. The result suggests that larger loans are related to higher cost efficiency and, therefore, profit. The results also show a positive relationship between borrowers per staff member and MFI sustainability. In short, Thai MFIs staff members are more efficient at managing borrowers as the number increases. This leads to MFI sustainability.

Total assets indicate MFIs' size. The results indicate that larger MFIs are less likely to lead to sustainability. One reason is that Thai MFIs do not experience economies of scale. MFIs have become too complex to manage; in short, diseconomies of scale occur when MFIs are too large. MFI staff members should pay more attention to strengthening their knowledge (e.g., financial management practices, lending strategies, credit appraisal and internal audit processes) (Aditto, 2016). Aditto (2016) suggests that MFIs should consider introducing appropriate short training courses for MFI staff members.

The debt to equity ratio assesses the use of commercial funds by MFIs. The results indicate that a higher debt to equity ratio is less likely to lead to MFI sustainability. Abdulai and Tewari (2017) explain that MFIs that increase their funds using debt are less likely to be sustainable because they have high financing costs from the debts.

The operating expense ratio shows a significant negative relationship with MFI sustainability. The operating expense ratio also reflects MFI efficiency. This study indicates that when the operating expense ratio is low, an MFI is running efficiently. In short, efficient management practices enable Thai MFIs to reach more clients and attain higher profit.

There is a significant positive relationship between yield on gross loan portfolio and MFI sustainability. The results indicate that an increase in yield on gross loan portfolio increases MFIs' sustainability in Thailand. The yield on gross loan portfolio indicates an MFI's efficiency in generating cash revenue from its outstanding portfolio (Woldeyes, 2012). The next chapter summarizes the study's major findings and research implications.

Chapter 6

Conclusions

This chapter summarizes the study. Section 6.1 presents a recap of the research objectives, the data used and methodology. Section 6.2 summarizes the major findings. Section 6.3 discusses the implications of the findings. Finally, section 6.4 discusses the research limitations and provides recommendations for future research.

6.1 Summary

The primary aim of this study was to identify individuals who participate in Thai microfinance programmes and investigate how these programmes impact on participants' economic and social welfare. A secondary aim of the study was to evaluate Thai MFIs' performance and investigate the factors that affect the sustainability of these programmes. This study had four objectives: (1) to explore the determinants of households' credit participation in Thailand; (2) to investigate the impact of microfinance programmes on the economic and social welfare of Thai households; (3) to evaluate the VF and SGP performance; and (4) to investigate the determinants that affect MFI sustainability.

Chapter 1 provided background information about Thai MFIs and outlined the differences between VFs and SGPs. Chapter 2 reviewed the literature on microfinance participation, the impact of microfinance programmes on the economic and social welfare of Thai households, MFI performance and sustainability. The literature review on microfinance for both theoretical and empirical models suggested that asymmetric information plays an important role in credit participation. The asymmetric information problem explains how the credit market works. The literature on the credit market argues that asymmetric information flows lead to adverse selection and moral hazard problems. Both problems lead to credit rationing. Credit rationing gives rise to credit constraints regardless of an individual's repayment ability. The demand for credit is used to explain households' behaviours by assuming that households maximize their utility level. The demand for credit plays an important role in understanding households' participation in the credit market.

Based on the literature review, microfinance impacts can be divided in two: the impact on economic welfare and on social welfare (Coleman, 2006). In terms of the economic welfare impact of microfinance, two common indicators are used: income and consumption (Hume, 2000). Under social welfare we included education and healthcare. The literature review concludes that there are problems with selection bias when evaluating microfinance impacts. Many studies use more than one method to overcome selection bias. This study used PSM and the fixed effect model to evaluate the impact of microfinance programmes.

There are three ways to assess MFIs' performance and sustainability: outreach, welfare impact and financial self-sustainability. This study focused solely on financial self-sustainability because financial self-sustainability covers the cost of funds and other forms of subsidies. Previous studies have used MFI characteristics, financial structure and financial performance to evaluate MFI performance. MFI characteristics include: age, total assets, total liability, total equity, the number of members, the number of borrowers, average loan balance per borrower, personnel, borrowers per staff member, loans per staff member, and profit. For financial structure, five criteria are identified in the literature: capital per asset ratio, debt per equity, deposit per loan, and gross loan portfolio per assets. For financial performance, this study used three criteria: ROA, ROE, and operational self-sufficiency, because financial performance covers these three ratios. In terms of MFI sustainability, the literature review showed that two indicators are commonly used to evaluate MFIs sustainability: operational self-sustainability and financial self-sustainability. This study focused on only financial self-sustainability because it covers the cost of funds and other forms of subsidies beside operational self-sustainability.

This study investigated the determinants that affect the financial self-sustainability of MFIs in Thailand using a panel regression model and panel data. The panel regression model was used because of its advantages over cross-section and time-series data methods (Kinde, 2012). Panel data involve the pooling of observations on a cross-section of units over several time periods. This can increase the degrees of freedom and, therefore, the power of the test (Kinde, 2012).

Chapter 3 discussed relevant issues in the microfinance literature (the theory of credit rationing, household credit demand, MFI sustainability and performance) to establish the empirical models for research objectives 1, 2, 3 and 4 discussed in Chapter 2. The theory of credit rationing explains how imperfect information creates the problem of credit rationing in the credit market. This problem leads to credit constraints. Given credit constraints, the demand for credit can be derived using the standard Ramsey Growth Model. This model shows how loans can improve individual or household utility through production and consumption and increase an individual's/household's welfare. Following the theory of credit rationing, household credit demand, MFI sustainability and performance, different empirical models to address different research objectives were discussed. First, this study investigated the determinants affecting a household's decision to participate in VF, SGP, both VF and SGP, or not participate. Our study used the multinomial logit model to determine household characteristics that affect microfinance participation. Next, we used PSM and fixed effect models to evaluate the impact of microfinance programmes on borrowers' social and economic welfare. These models were chosen to obtain unbiased and consistent estimators. Chapter 3 also discussed MFI financial performance and sustainability. This chapter compared VF and SGP performance in terms of MFI characteristics, financial structure and financial performance. This study

used these parameters because they are comprehensive and are globally accepted indicators of financial performance for MFIs (Agarwal & Sinha, 2010). In terms of MFI sustainability, this study used the panel regression technique, which involved pooling observation units in cross-sectional data over several time periods to investigate the determinants that affect MFI sustainability.

Chapter 4 investigated microfinance participation and microfinance impact. It is important to understand the determinants of households' credit participation and the impact of microfinance programmes because these results are crucial towards developing effective microfinance products and services that can help reduce poverty (Cintina & Love, 2014; Hermes & Meesters, 2011). Chapter 5 evaluated MFI performance and sustainability. This chapter determined how well MFIs are doing financially and how to improve the institutions' future performance. This study used different techniques to analyse the data. First, a multinomial logit model was used to investigate the determinants affecting household participation in microfinance programmes. PSM and fixed effect models were chosen because they can overcome observed and unobserved biases. Having controlled for bias using observed covariates, PSM was applied to estimate the impact of microfinance programmes on households using cross-sectional data. The fixed effect model with PSM was applied on the panel data set to control both observed and unobserved biases in the impact estimators of microfinance programmes. Before the fixed-effect model was estimated, PSM was applied to remove any possible biases. The objective of PSM is to eradicate observed heterogeneity in the initial period, before using the fixed effect model (Heckman et al., 1997). For MFI performance, this study analysed and compared both VF and SGP performance using all 11 characteristics identified in the literature, financial structure and financial performance. This study used descriptive statistics to assess VFs' and SGPs' performance. Finally, a panel regression model was used to identify determinants of MFI financial self-sustainability. The study's findings are summarized in the next section.

6.2 Major Findings

In the analysis of microfinance participation, VFs serve low-income households in rural areas. However, VFs do not reach the poor. Households with higher dependency ratios are less likely to borrow from VFs. This finding suggests that VFs cannot help households that are less economically active. Most VF borrowers can access other loan sources when they need to obtain emergency loans. This indicates that the VF programme is only one source of credit for individuals in rural areas. The programme also provides loans to elderly and low-educated household heads. VFs target women. Larger households are more likely to access VFs. VFs also grant loans to formal and informal workers.

In contrast, SGPs grant loans to well-educated, young household heads in regional areas. SGP borrowers have higher household incomes than VF ones. These borrowers can also access other

loans. This shows that SGP borrowers can access other forms of credit. Larger households are more likely to participate in SGPs. SGP borrowers are more likely to be entrepreneurs than farmers.

VF and SGP borrowers are low-educated and female household heads in rural areas. These borrowers can access other loans when they have an emergency. Larger households and households that own their own motorcycles have a higher probability of borrowing from both programmes. Both VF and SGP borrowers are employed in a range of jobs: farmers, entrepreneurs and in both formal and informal occupations.

Our findings indicate that VFs and SGPs are credit sources in the rural credit market; these sources help rural households access credit to meet their needs (Yostrakul, 2018). In addition, rural Thai households borrow from many sources so that they can rotate their loan repayments. Low-income households refinance their loans by borrowing from different sources. This practice enables them to maintain good credit ratings (Hickson et al., 2013).

This study used PSM models to estimate the welfare impact of VF and SGP participation on income and expenditure. VFs impact income, educational, and transport expenditure, but not food, housing and medical expenditure. VFs have a negative impact on income, educational, and transport expenditure. Our findings are similar to previous studies (e.g., Chandoevrit & Ashakul, 2008). One reason is that VF loans are not large enough to enhance income, educational, and transport expenditure (Chandoevrit & Ashakul, 2008). This study finds that SGPs' effects are significant in increasing income but not significant in terms of housing, food, medicine, educational, and transport expenditure. This indicates that SGP borrowers effectively invest their loans in income-generating activities, such as agricultural production and self-employment. This suggests that SGPs achieve their objective of supporting borrowers to invest in economic activities (Luxchaikul, 2014).

PSM is an effective method to control bias because of observed determinants in impact evaluation. However, PSM cannot control for unobserved characteristics. Panel data can control for unobserved bias. This study used the fixed effect model with PSM to evaluate the impact of VFs and SGPs on household income and housing, food, medicine, educational, and transport expenditure. The results show that the VF impacts only on educational expenditure; i.e., borrowers spend more money on their children's education. Rural Thai households, especially farmers, do not have much surplus money. To pay bills, like children's school fees, they often need to borrow money. However, VF loans are short-term (only a year), which means that increased educational expenditure does not reduce a household's poverty. If education were truly free, households would be able to spend the loans on income generating activities (Fongthong, 2013).

The fixed effect model with PSM results show SGPs' impact on income and transport expenditure. This indicates that SGP borrowers invest their loans on working capital and assets that enable them to earn more money. SGP loans also affect transport expenditure. Cars and motorcycles are necessary production inputs (Kaboski & Townsend, 2012). Rural households use these vehicles to transport products from remote areas to their shops (Awan & Juiya, 2015). This suggests that a common purpose of household borrowing is transport expenses, related to work investment (Awan & Juiya, 2015; Karlan & Zinman, 2010). Households need access to convenient transport to complete their activities, e.g., going to school, getting to work, meeting friends, and buying items at the market (Fongthong, 2013). High household transport costs may imply that a household has a lot of activities to accomplish.

To meet the third objective (examine MFI performance), this study compared VFs and SGPs in terms of age, total assets, total liability, total equity, the number of members, the number of borrowers, average loan balance per borrower, personnel, borrowers per staff member, loans per staff member, and profit), financial structure, and financial performance. We find that both VFs and SGPs could benefit from organizing learning because VFs and SGPs have been operating for an average of 13.09 and 10.61 years, respectively. Organizational learning is a process within a specific organization that involves the interaction of multiple levels of analysis (individual, group, organizational and inter-organizational). Productivity and efficiency improvement can be achieved via organizational learning (Kar, 2012). SGPs are bigger than VFs in terms of the average number of members and borrowers. However, VFs provide more loans than SGPs to poorer clients. In loan management, SGP staff are more efficient than VF staff. SGPs' profits are significantly higher than VFs' profits.

In financial structure, SGPs' assets are significantly higher – twice as much as VFs'. SGPs also have significantly higher liabilities than VFs, approximately 36 times. One reason why SGPs have higher liabilities than VFs is that SGPs are funded through member deposits. In contrast, VFs receive government subsidies. This can be seen by VFs' high equity and low liability. The VFs' capital per asset ratio is significantly higher than SGPs'. Both the VF and SGP capital per asset ratios are above the Global and FSS benchmarks. The capital per asset ratio is used to evaluate MFI solvency. This ratio also shows an MFI's ability to meet its obligations and absorb unexpected losses (Yenesew, 2014). If an MFI has a higher capital per asset ratio, it is safer than a lower ratio institution. The finding indicates that both VFs and SGPs are safe compared with the Global and FSS benchmarks. In short, both VFs and SGPs can meet their obligations and absorb unexpected losses. The SGP debt per equity ratio is significantly higher than the VF one. This indicates that SGPs are savings-based organizations. We also found that the SGP deposits per loans ratio is higher than the Global and FSS benchmarks, but VFs one is lower than the benchmarks. This suggests that SGPs depend more on depositor funds, their primary source of funding. External funding is more costly than deposits. Thus,

MFIs may effectively use local deposits (Muriu, 2011). The gross loan portfolio per assets ratio indicates that both VFs and SGPs have lending as their core earning asset. Our results indicate that both VFs and SGPs are profitable and financially sustainable. The determinants that affect Thai MFI sustainability are: average loan balance per borrower, borrowers per staff member, total assets, debt to equity ratio, the operating expense ratio, and the yield on the gross loan portfolio.

There is a positive relationship between average loan balance per borrower and MFI sustainability. In short, MFIs profitability is associated with greater loan size. This means that larger loans are more cost efficient and, therefore, more profitable. The average loan balance per borrower is used as a proxy measure for depth of outreach (Adongo & Stork, 2005; Cull et al., 2007; Nyamsogoro, 2010). Smaller loans indicate poorer borrowers (Adongo & Stork, 2005; Cull et al., 2007; Nyamsogoro, 2010). The results indicate that Thai MFIs do not lend money to the very poor. The findings also indicate that the number of borrowers per staff member is a significant positive factor affecting MFI sustainability. The greater the number of clients an MFI serves, the more efficient it is. This result indicates that Thai MFIs' staff are more efficient at managing borrowers when their number increases. This leads to greater MFI sustainability. MFIs have a simple committee structure, with a chairperson, a vice-chair, a treasurer, secretary, and several members (Boonperm et al., 2013; Meagher, 2013). Village residents vote for individual management committee members. This process shows that village residents and management committee members know each other well (Meagher, 2013).

For financial structure, the results show a significant negative relationship at the 1% level between total assets and MFI sustainability. This suggests that larger total assets decrease MFI sustainability. Our result implies that large MFIs do not benefit from economies of scale. Diseconomies of scale might occur because of the existence of a bureaucratic bottleneck and inefficient asset management (Yenesew, 2014). Diseconomies of scale lead to increased unit costs because MFIs get too large or expand too quickly (Ngo, 2012). The results also show that the debt to equity ratio is significantly negative at the 5% level. This result implies that a higher debt to equity ratio is less likely to lead to MFI sustainability. This means that if MFIs are more debt-financed (compared with other sources of finance), they are less sustainable. This result implies that a combination of capital sources does not improve an MFI's FSS.

The results show that there is a significant negative relationship at the 5% level between the operating expense ratio and MFI sustainability. A higher operating expense ratio is associated with decreased MFI sustainability. The lower an MFI's operating expense ratio, the more efficient it is. In short, if the operating expense ratio is low, it is operating efficiently (Nyamsogoro, 2010).

The yield on gross loan portfolio variable is positive and significant at the 1% level in terms of MFI sustainability. This result suggests that an increase in yield on gross loan portfolio increases MFI sustainability. This indicates that Thai MFIs are efficient in generating cash revenue from their outstanding portfolios.

6.3 Implications of the Study

The results of our study have several important implications for academics and policymakers, particularly those working in the area of microfinance.

6.3.1 Academic Implications

Given the existence of asymmetric information, MFI financial service provisions are not optimal solutions. To make the microfinance market work more effectively, the government and village leaders who manage and/or oversee microfinance programmes should focus on solutions to reduce asymmetric information problems and associated costs (Hao, 2005). For MFIs, financial innovations are essential to solve asymmetric information problems. Innovation in financial technologies include group lending, credit rating and credit scoring agencies (Hao, 2005). Group lending is the practice of individuals coming together to obtain loans (Armendariz de Aghion & Morduch, 2005). This form of borrowing reduces MFI transaction costs. Credit rating and credit scoring agencies help increase information and reduce the costs related to the provision of financial services (Hao, 2005). MFIs work with these agencies in partnership with social and informational intermediaries (Hao, 2005). The government should enhance the development of financial infrastructure and information intermediation.

To achieve MFI sustainability, MFIs should make sure their social and financial goals are adequately balanced. We propose that MFIs use a mixed approach. We recommend that MFIs follow profit maximization principles and that the government and donors support this approach in two ways. First, they should create a robust financial infrastructure. This will require the participation of information intermediaries to assist MFIs to reduce their costs, e.g., credit rating, credit bureaus or credit scoring agencies. Secondly, the government should provide social intermediaries for the poor, e.g., they should offer education, job creation, physical infrastructure, and business skills to the poor to enable them to access to financial institutions (Hao, 2005). These services would help the poor to participate in financial services (Hao, 2005).

6.3.2 Policy Implications

Our results show a positive relationship between VFs and educational expenditure. In short, VFs help rural households obtain loans to invest in their children's schooling. Investment in education is

important because it helps to break the vicious poverty cycle. This study also found that SGPs impact income and transport expenditure. These findings indicate that SGP loans can improve rural livelihoods and support poverty reduction.

Our results show that the VF targets certain individuals, that is, low-income rural households, those with older or female household heads and/or those households with lower levels of education. Households who are well-educated and those households who have young household heads in regional areas are more likely to borrow money from SGPs. SGP borrowers have higher household incomes than VF borrowers. This result shows that both VFs and SGPs do not encourage the extremely poor to participate in MFI schemes.

For low-income households, improving microfinance participation can start from the households themselves; households should participate in credit groups and improve their work-skills and education. Education can be used to raise collateral-free borrowers' creditworthiness, and work skills can guarantee that borrowers will repay their loans (Phan, 2012). However, MFIs do not benefit from including the very poor because poor people need pre-support, such as special aids and community support, to overcome internal rationing. Internal credit rationing is associated with the demand for credit. Internal credit rationing refers to a borrower's acts of self-rationing (asking for the smallest possible loan). Extremely poor people often suffer from illness and/or a lack of skills or education. As MFIs are designed to lend money for income generating activities, the very poor are unlikely to be granted loans. Thus, microfinance programmes will not be an effective solution for this group of people; the extremely poor require both welfare and microfinance programmes (Phan, 2012). Microfinance programme participation would therefore be the next step after the very poor receive pre-support and provide evidence of their ability to work. Thai MFIs can use the Central Public Database from the Revenue Department, the Ministry of Finance, to identify poor people. The database is a personal income database that facilitates more effective targeting of low-income earners (NESDB, 2017). This database can identify the extremely poor who receive government benefits such as financial assistance, free public transport and food coupons. This strategy will help microfinance programmes reach the real poor who really need loans to improve their livelihoods.

Our findings indicate that VFs and SGPs are major credit sources in Thailand rural credit market. These sources enable rural households to access credit to meet their needs. Rural Thai households borrow from many sources so that they can rotate their loan repayments. Low-income households refinance their loans by borrowing from different sources. This practice means that Thai households have multiple sources of debt leading to high levels of debts. The government should provide training courses on financial management and financial literacy to households who are struggling with financial issues or owe money to multiple lenders. The government should target households which

are most likely to have poor financial health. They should develop campaigns around financial health and encourage the target group to engage in budgeting practices (Chotewattanakul, 2019). This activity will help such households to better manage their cash flow and create savings plans. By putting money aside, households are better able to deal with future income shocks (Chotewattanakul, 2019).

In terms of sustainability, our study finds that staff member productivity and operating expense are the determinants affecting MFIs' sustainability. Our study suggests that MFIs should embrace technology to minimize their transaction costs. MFIs can use management information software and other innovative banking technologies; e.g., internet banking, mobile phone banking, smart card operation, and credit scoring. These tools can decrease administrative costs, increase staff productivity and improve financial accounts' reliability (Muriu, 2011). MFI staff should learn to use modern technology. In the first stage, the CDD and GSB should select MFIs that can afford advanced technology. GSB and BAAC should train MFI staff in how to use the new technologies. In addition, MFIs should be aware of the possibility of data breaches (or the privacy of MFI clients), when using new technologies; e.g., mobile banking and branchless micro-banking (Muriu, 2011). Therefore, MFIs should identify best practice and the most cost-effective ways of using new technology. New technology can improve MFI profitability in an increasingly competitive microfinance sector (Muriu, 2011).

The evidence around MFIs' funding choices calls for the development of appropriate regulatory policies that can help MFIs access long-term debt to improve their performance. These policies should include laws that help MFIs access the capital market. In addition, MFIs should mobilize deposits to lower operation costs. Deposits provide MFIs with an inexpensive, sustainable source of funds for lending, assuming the deposit programme is cost-efficient. However, MFIs need to have a license to accept public deposits which means they would need to comply with certain regulations. A larger ratio of loans to total assets translates into more interest revenue and, therefore, greater profitability (Muriu, 2011).

6.4 Limitations and Future Research

This current study has several limitations. Some of these limitations provide the basis for recommendations for future research.

The current study investigated only the impact of semi-formal microfinance programmes in Thailand. Our methodologies should be applied to other sources of credit, e.g., those offered through the BAAC and informal credit such as Sajja Saving Groups and Village banks. The results indicate that Thai households can access many sources of credit. Households with multiple sources of credit have high

debt levels. As Thai households often borrow from formal credit sources to pay other (informal) debts, this can become a vicious cycle. However, high debt levels or multiple sources of credit are not always an indication of financial distress; many microcredit programmes have a credit limit so households may borrow from multiple credit sources to have enough capital to invest in income generation activities. Therefore, future study should investigate if multiple sources of credit can improve household income and expenditure or whether this simply perpetuates the poverty cycle.

Future research could examine the dynamic impact of microfinance programmes. A microfinance impact study that takes in to account the effect of past credit and the length of microfinance participation would be helpful because the impact of microfinance programmes is believed to be related to previous loans and the length of microfinance participation. It is important to understand the dynamics of microfinance expansion and its impact on household welfare (Khandker & Samad, 2014). The dynamic impact of microfinance programmes can accurately confirm the programme effect beyond the participation period. Confirmation of the dynamic impact of microfinance programmes provides further of evidence whether the programme impacts accrue beyond the participation period (Khandker & Samad, 2014; Phan, 2012).

This study shows that community leaders and staff in rural areas are vital to MFIs' operations. There is little/no research on the impact of community leaders and staff on MFI sustainability. In addition, social capital roles (defined as social networks, norms, and trustworthiness) in the community play an important role in enhancing MFI performance. Future research should examine the effect of social capital on MFI sustainability.

The current study used annual MFI reports. These reports lack comparable accounting standards. This problem creates limitations for a cross-Thai MFI analysis. Many MFIs do not have the necessary knowledge to compile annual reports. This study used annual reports from well-performing MFIs. Therefore, the current study found that both VFs and SGPs are profitable and financially sustainable. However, we were unable to collect many MFI annual reports because the government does not currently have a database that contains this information. If the current study had used a broader sample, the results may have been different.

Operation cost limitations: In Thai MFIs, operation costs do not reflect the real costs. Most Thai MFIs do not have major operating costs because their staff members are volunteers, i.e., they do not earn wages. VFs are administered at two levels (national and village level) (Meagher, 2013). The national level works with volunteers (VF members from each village). These volunteers deal directly with the funds. The evidence shows that the minimum value of the operating expense ratio is zero. Future research should include all MFI operational costs.

There are several questions that this study has not answered. One example is how new financial technologies could be installed. Financial technologies may enhance information availability and these technologies can decrease administrative costs, increase staff productivity and improve MFIs' profitability (Muriu, 2011). Future research could also explore how social intermediation could be developed and how it would contribute to financial intermediation. Future research might also examine how MFIs can balance their financial and social goals.

References

- Abdulai, A., & Tewari, D. D. (2017). Trade-off between outreach and sustainability of microfinance institutions: evidence from sub-Saharan Africa. *Enterprise Development and Microfinance*, 28(3), 162-181.
- Abou-Ali, H., El-Azony, H., El-Laity, H., Haughton, J., & Khandker, S. (2010). Evaluating the impact of Egyptian Social Fund for Development programmes. *Journal of Development Effectiveness*, 2(4): 521–55.
- Aditto, S. (2016). Microfinance system in Thailand. In C. Gan & G. V. Nartea (Ed.), *Microfinance in Asia* (pp. 147-175). New Jersey : World Scientific.
- Adjei, J. K., Arun, T., & Hossain, F. (2009). *The role of microfinance in asset building and poverty reduction: The case of Sinapi Aba Trust of Ghana*. Manchester: Brooks World Poverty Institute.
- Adongo, J. and Stork, C. (2005). *Factors influencing the financial sustainability of selected microfinance institutions in Namibia*. NEPRU Research Report No 38, ISSN 1026-9258.
- Agarwal, P. K., & Sinha, S. K. (2010). Financial performance of microfinance institutions of India. *Delhi Business Review*, 11(2), 37-46
- Akerlof, G. (1970). The market for lemons: Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84, 488-500
- Akihiko, O. (2015). Saving Groups and rural financial markets: Japanese and Thai experiences. *Southeast Asian Studies*, 3(Supplementary Issue), 15-38.
- Aktaruzzaman, K., & Farooq, O. (2016). Impact of microcredit on borrowers' expenditures: A fuzzy regression discontinuity design approach. *Applied Economics*, 48(38), 3685-3694.
- Alexander-Tedeschi, G., & Karlan, D. (2002). *Microfinance impact: Bias from dropouts*. Connecticut: Yale University.
- Anduanbessa, T. (2009). Statistical analysis of the performance of microfinance institutions: The Ethiopian case. *Savings and Development*, 2(33), 183–198.
- Argote, L., & Miron-Spektor, E. (2011). Organization learning: From experience to knowledge. *Organization Science*, 22(5), 1123-1137.
- Armendariz de Aghion, B., & Morduch, J. (2004). Microfinance: Where do we stand? In Charles Goodhart (Ed.), *Financial Development and Economic Growth: Explaining the Links*, London: Macmillan/ Palgrave.
- Armendariz de Aghion, B., & Morduch, J. (2005). *Economics of Microfinance*. Cambridge, England: MIT Press.
- Arthur, S., Abanis, T., Eliab, B., & Sumil, N. (2013). Financial performance in the selected microfinance institutions in Uganda. *International Journal of Engineering Research and Technology*, 2(2), 1-11.
- Arun, T., Imai, K., & Sinha, F. (2006). Does the microfinance reduce poverty in India? Propensity score matching based on a national level household data. *Economics Discussion Paper, The University of Manchester*.

- Ashraf, M. A. & Ibrahim, Y. B. (2014). Poverty alleviation and identifying the barriers to the rural poor participation in MFIs: A case study in Bangladesh. *Journal of Economic Cooperation and Development*, 35(3), 99-132.
- Asian Development Bank [ADB]. (2019). *Poverty in Thailand*. Retrieved from <https://www.adb.org/countries/thailand/poverty>
- Augsburg, B., De Haas, R., Harmgart, H., & Meghir, C. (2015). The impacts of microcredit: Evidence from Bosnia and Herzegovina. *American Economic Journal: Applied Economics*, 7(1), 183–203.
- Awan, A. G., & Juiya, M. J. I. (2015). Role of microfinance in poverty alleviation: Evidence from Pakistan. *American Journal of Trade and Policy*, 2(1), 37-44.
- Balogun, O.L. & Yusuf, S.A. (2011). Determinants of demand for microcredit among the rural households in South-Western States, Nigeria. *Journal of Agricultural and Social Sciences*, 7, 41–48.
- Banerjee, A., Duflo, E., Glennerster, R., & Kinnan, C. (2015). The miracle of microfinance? Evidence from a randomized evaluation. *American Economic Journal: Applied Economics*, 7(1), 22–53.
- Barry, P. J., Ellinger, P. N., Hopkin, J. A., & Baker, C. B. (1995). *Financial Management in Agriculture* (Fifth Edition). Illinois, USA: Interstate Publishers.
- Bassem, B. S. (2012). Social and financial performance of microfinance institutions: Is there a trade-off? *Journal of Economics and International Finance*. 4(4), 92–100. doi: 10.5897/JEIF11.129^[1]_{SEP}
- Bayai, I., & Ikhide, S. (2016). Financing and financial sustainability of microfinance institutions (MFIs): a conceptual view. *Bank and Bank Systems*, 11(2), 21-32.
- Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In R. W. Hall (Ed.), *The Handbook of Transportation Science* (pp. 5-33). Springer, Boston, MA.
- Bhuiyan, A., Siwar, C., Ismail, A. G., & Talib, B. (2011). Financial sustainability and outreach of MFIs: A comparative study of AIM in Malaysia and RDS of Islamic Bank Bangladesh. *Australian Journal of Basic and Applied Sciences*, 5(9), 610-619.
- Bird, K., Hattel, K., Sasaki, E., & Attapich, L. (2011). *Poverty, income inequality, and microfinance in Thailand*. Asian Development Bank. Retrieved from <http://hdl.handle.net/11540/1311>. License: CC BY 3.0 IGO.
- Blundell, R., Dearden, L., & Sianesi, B. (2005). Evaluating the effect of education on earnings: models, methods and results from the National Child Development Survey. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 168(3), 473-512.
- Bogan, L.V. (2012). Capital structure and sustainability: An empirical study of microfinance institutions. *A Review of Microfinance and Statistic*, 94(4), 1045-1058.
- Boonperm, J., Haughton, J., & Khandker, S. R. (2013). Does the Village Fund matter in Thailand? Evaluating the impact on incomes and spending. *Journal of Asian Economics*, 25, 3-16.
- Burgess, R., & Pande, R. (2002). Do rural banks matter? Evidence from the Indian social banking experiment. *Paper prepared for the International Monetary Fund's conference on Macroeconomic Policies and Poverty Reduction*, Washington, D.C., March 14–15.
- Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometric Using Stata*. USA: Stata Press Publication.

- Carreras, F. J. G. (2012). *Does microfinance have an impact? Three quantitative approaches in rural areas of Bangladesh and Andhra Pradesh, India*. (Unpublished doctoral thesis). University of Sussex, Sussex, England.
- Caliendo, M. (2006). *Microeconometric Evaluation of Labour Market Policies*. Springer Verlag.
- Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1), 31-72.
- CGAP. (2003). *Microfinance Consensus Guidelines: Guiding Principles on Regulation and Supervision of Microfinance*. Washington, DC: Consultative Group to Assist the Poor (CGAP).
- Chandoevwit, W., & Ashakul, B. (2008). The impact of the Village Fund on rural households. *TDR Quarterly Review*, 23(2), 9-16.
- Chen, Z., & Jin, M. (2017). Financial inclusion in China: Use of credit. *Journal of Family and Economic Issues*, 38(4), 528-540.
- Cheng, E. J. (2006). *The demand for micro-credit as a determinant for microfinance outreach - evidence from China*. ACESA Annual Conference 2006 Emerging China: Internal Challenges and Global Implications, Centre for Strategic Economic Studies, Victoria University, Melbourne, Australia.
- Chotewattanakul, P. (2019). *The determinants of household indebtedness: Household-level evidence from Thailand*. (Unpublished doctoral thesis). University of New South Wales, Canberra, Australia.
- Cintina, I., & Love, I. (2014, September). The miracle of microfinance revisited: Evidence from Propensity Score Matching. *University of Hawai'i at Manoa, Department of Economics*, Working paper No. 14-24.
- Coleman, B. E. (1999). The impact of group lending in northeast Thailand. *Journal of Development Economics*, 60(1), 105-141.
- Coleman, B. E. (2006). Microfinance in northeast Thailand: Who benefits and how much? *World Development*, 34(9), 1612-1638. doi:10.1016/j.worlddev.2006.01.006
- Conning, J., & Udry, C. (2007). Rural financial markets in developing countries. *Handbook of Agricultural Economics*, 3, 2857-2908.
- Cooperatives Promotion Department [CPD]. (2019). *Annual statistics of cooperatives, agricultural groups and vocational groups in Thailand 31st December 2018*. Retrieved from <https://app1.cpd.go.th/annual-statistics-of-cooperatives-31122561/mobile/index.html#p=1>
- Copestake, J. (2007). Mainstreaming microfinance: Social performance management or mission drift? *World Development*, 35(10), 1721-1738.
- Crépon, B., Devoto, F., Duflo, E., & Parienté, W. (2015). Estimating the impact of microcredit on those who take it up: Evidence from a randomized experiment in Morocco. *American Economic Journal: Applied Economics*, 7(1), 123-50.
- Crombrugghe, A., Tenikue, M., & Sureda, J. (2008). Performance analysis for a sample of microfinance institutions in India. *Annals of Public and Cooperative Economics*, 79(2), 269-299.
- Cull, R., Demircuc-Kunt, A., & Morduch, J. (2007). Financial performance and outreach: a global analysis of leading microbanks. *The Economic Journal*, 117(517).

- Cull, R., Demirguc-Kunt, A., & Morduch, J. (2016). The microfinance business model: Enduring subsidy and modest profit. *Policy Research Working Paper 7786*. Washington, D.C.: The World Bank.
- Cull, R., Demirguc-Kunt, A., & Morduch, J. (2018). The microfinance business model: Enduring subsidy and modest profit. *The World Bank Economic Review*, 32(2), 221-244.
- Cuong, N. V. (2008). Is a governmental micro-credit program for the poor really pro-poor? Evidence from Vietnam. *The Development Economies*, 46(2), 151-187.
- Dadson, A. V., Abankwah, V., & Kwansah, J.K.K. (2012). Women participation in microcredit and its impact on income: A study of small-scale businesses in the central region of Ghana. *American Journal of Experimental Agriculture*, 2(3), 502-515.
- Dehejia, R. H. (2005). Practical propensity score matching: a reply to Smith and Todd. *Journal of Econometrics*, 125(1-2), 355-364.
- Dehejia, R. H., & Wahba, S. (2002). Propensity score matching methods for nonexperimental causal studies. *Review of Economics and Statistics*, 84(1), 151-161.
- Diagne, A. (1999). *Determinants of household access to and participation in formal and informal credit markets in Malawi*. Discussion Paper No. 67, Food Consumption and Nutrition Division, International Food Policy Research Institute, Washington, D.C.
- Diagne, A., and M. Zeller (2001). *Access to Credit and Its Impact on Welfare in Malawi*. Research Report No. 116. Washington, DC: International Food Policy Research Institute.
- Dissanayake, D. M. N. S. W. (2012). The determinants of microfinance profitability: Evidence from Sri Lankan microfinance institutions. *Kelaniya Journal of Management*, 1(1), 50-67.
- Doan, T., Gibson, J., & Holmes, M. (2010). What determines credit participation and credit constraints of the poor in peri-urban areas, Vietnam?. *Munich Personal RePEc Archive, Paper No. 27509*.
- Dufhues, T., Buchenrieder, G. & Munkung, N. (2013) Social capital and market imperfections: Accessing formal credit in Thailand. *Oxford Development Studies*, 41(1), 54-75. doi: 10.1080/13600818.2012.753999
- Dunford, C. (2003). *The Holy Grail of Microfinance: Helping the Poor and Sustainable: Microfinance Evolution, Achievements and Challenges*. ITDG, London.
- Durojaiye, A. M., Yusuf, S. A., & Balogun, O. L. (2014). Determinants of demand for microcredit among grain traders in Southwestern states, Nigeria. *Journal of Agriculture and Veterinary Science*, 7(11), 1-9.
- El-Maksoud, S. A. (2016). *Performance of microfinance institutions*. (Unpublished doctoral thesis). Cardiff Metropolitan University, Cardiff, England.
- Eularie, M., & Vishwanatha, V. (2016). An evaluation of the factors influencing small farmers' access to microcredit in Rwanda: An application of multinomial logit. *International Journal in Multidisciplinary and Academic Research*, 5(4), 1-21.
- Eur-U-Sa, A. (2011). *Measuring performance of Bank of Agricultural and Agricultural Cooperative (BAAC), Thailand; Relationships between institutional goals and future trend*. (Unpublished Master's thesis). Ritsumeikan Asia Pacific University, Japan.
- Evans, T. G., Adams, A. M. & Mohammed, R. (1999). Demystifying nonparticipation

- in microcredit: a population-based analysis. *Journal of World Development*, 27(2), 419-430.
- Fongthong, S. (2013). *An economic analysis of microcredit of village and urban community funds in Thailand*. (Unpublished doctoral thesis). Chiang Mai University, Chiang Mai, Thailand.
- Fongthong, S., & Suriya, K. (2014). Determinants of borrowers of the Village and Urban Community Fund in Thailand. *CMUJ of Social Sciences and Humanities*, 1(1), 21-37. doi: 10.12982/cmujASR.2014.0002
- Freese, J., & Long, J. S. (2000). Test for the multinomial logit model. *Stata Technical Bulletin*, 58, 19-25.
- Gan, C., Nartea, G. V., & Garay, A. (2007). Credit accessibility of small-scale farmers and fisherfolk in the Philippines. *Review of Development and Cooperation*.
- Ghosh, P., Mookherjee, D., & Ray, D. (2000). Credit rationing in developing countries: An overview of the theory. In: Mookherjee, D., Ray, D. (Eds.), *Readings in The Theory of Economic Development*. Blackwell, Malden, MA, 283–301.
- Greene, W. H. (2003). *Econometric Analysis* (5th ed.). Upper Saddle River, N.J.: Prentice Hall.
- Hao, Q. M. (2005) *Access to Finance and Poverty Reduction an Application to Rural Vietnam*. (Unpublished doctoral thesis). University of Birmingham, Birmingham, England.
- Hausman, J., & Mcfadden, D. (1984). Specification tests for the multinomial logit model. *Econometrica*, 52(5), 1219-1240.
- Heckman, J., Ichimura, H., & Todd, P. (1997). Matching as an econometric evaluation estimator. *Review of Economic Studies*, 65, 261-294.
- Hermes, N., & Lensink, R. (2011). Microfinance: Its impact, outreach, and sustainability. *World Development*, 39(6), 875-881.
- Hermes, N., Lensink, R., & Meesters, A. (2008). Outreach and efficiency of microfinance institutions. *World Development*, 39(6), 938–948.
- Hermes, N., & Meesters, A. (2011). The performance of microfinance institutions: Do macro conditions matter? In B. Armendáriz & M. Labie (Ed.), *The Handbook of Microfinance* (pp. 173-201). World Scientific Publishing.
- Hickson, R., Pochanukul, P., & Achavanuntakul, S. (2013). *Quality demand-side research report*. Kingdom of Thailand: Development of a strategic framework for financial inclusion in Thailand. Asian Development Bank.
- Hossain, M. S., & Khan, M. A. (2016). Financial sustainability of microfinance institutions (MFIs) of Bangladesh. *Developing Country Studies*, 6(6), 69-78.
- Hsiao, C. (2007), *Analysis of Panel Data*. (2nd ed.). New York, USA: Cambridge University Press.
- Hulme, D. (2000). Impact assessment methodologies for microfinance: Theory, experience and better practice. *World Development*, 28(1), 79-98.
- Imai, K. S., & Azam, MD. S. (2012). Does microfinance reduce poverty in Bangladesh? New evidence from household panel data. *The Journal of Development Studies*, 48(5), 633-653.
- Islam, A. (2011). Medium- and long-term participation in microcredit: An evaluation using a new panel dataset from Bangladesh. *American Journal of Agricultural Economics*, 93(3), 847–66.

- Islam, T. (2007). *Microcredit and Poverty Alleviation*. Aldershot, England; Burlington, U.S.A.: Ashgate Publishing.
- Jitsuchon, S. (1989). *Alleviation of rural poverty in Thailand*. Thailand Development Research Institute Working Paper submitted to Asian Regional Team for Employment Promotion, International Labour Organisation.
- Kaboski, J. P., & Townsend, R. M. (2012). The impacts of credit on village economies. *American Economic Journal: Applied Economics*, 4(2), 98-133.
- Kar, A. K. (2012). Does capital and financing structure have any relevance to the performance of microfinance institutions? *International Review of Applied Economics*, 26(3), 329-348. doi: 10.1080/02692171.2011.580267
- Karlan, D. (2001). Microfinance impact assessments: The perils of using new members as a control group. *Journal of Microfinance*, 3(2), 75-85.
- Karlan, D., & Zinman, J. (2010). Expanding credit access: Using randomized supply decisions to estimate the impacts. *The Review of Financial Studies*, 23(1), 433-464.
- Kasali, T. A., Ahmad, S. A., & Ean, L. H. (2016). Determinants of microcredit access: Empirical analysis from South-West Nigeria. *Journal of Economic Cooperation and Development*, 37(2), 128-148.
- Keeton, W. (1979). *Equilibrium Credit Rationing*. New York, USA: Garland Publishing Inc.
- Kereta, B. B. (2007). *Outreach and financial performance analysis of microfinance institutions in Ethiopia*. Paper presented at the African Economic Conference, United Nations Conference Centre (UNCC).
- Khan, Z. A., Butt, S., & Khan, A. A. (2017). Determinants of financial self sufficiency in microfinance institutions: A study of Pakistan, India and Bangladesh. *European Online Journal of Natural and Social Sciences*, 6(2), 296-301.
- Khandker, S. R. (2005). Microfinance and poverty. Evidence using panel data from Bangladesh. *World Bank Economic Review*, 19(2), 263-286.
- Khandker, S. R., & Faruquee, R. R. (2003). The impact of farm credit in Pakistan. *Agricultural Economics*, 28(3), 197-213.
- Khandker, S. R., Koolwal, G. B., & Samad, H. A. (2010). *Handbook on Impact Evaluation: Quantitative Methods and Practices*. World Bank. doi: 10.1596/978-0-8213-8028-4
- Khandker, S. R., & Samad, H. A. (2014). Dynamic effects of microcredit in Bangladesh. *Policy Research Working Paper 6821, the World Bank*.
- Kinde, B. A. (2012). Financial sustainability of microfinance institutions (MFIs) in Ethiopia. *European Journal of Business and Management*, 4(15), 1-10.
- Kislat, C., & Menkhoff, L. (2012). The village fund loan: Who gets it, keeps it and loses it? *Diskussionspapiere no. 490, der Wirtschaftswissenschaftlichen Fakultät, Universität Hannover*.
- Kono, H., & Takahashi, K. (2010). Microfinance revolution: Its effects, innovations, and challenges. *The Developing Economies*, 48(1), 15-73. doi: 10.1111/j.1746-1049.2010.00098.x
- Koppelman, F. S., & Bhat, C. (2006). A self instructing course in mode choice modeling: Multinomial and nested logit models. *U.S. Department of Transportation Federal Transit Administration*.

- Ledgerwood, J. (1998). *Microfinance Handbook an Institutional and Financial Perspective*. The World Bank, Washington, D.C.
- Lechner, M. (2000). A note on the common support problem in applied evaluation studies. *Swiss Institute for International Economics and Applied Economic Research, University of St. Gallen*.
- Lensink, R., & Pham, T. (2008). *Is microfinance an important instrument for poverty alleviation? The impact of microcredit programs on self employment profits in Vietnam*. Department of Finance, Faculty of Economics and Business University of Groningen, the Netherlands.
- Lewis, S., Tambunlertchai, K., Suesuwan, E., Adair, M., & Hickson, R. (2013). *Microfinance supply-side assessment report*. Asian Development Bank.
- Li, X. (2010). *An empirical analysis of microcredit on China rural household*. (Unpublished doctoral thesis). Lincoln University, Lincoln, New Zealand.
- Li, X., Gan, C., & Hu, B. (2011a). Accessibility to microcredit by Chinese rural households. *Journal of Asian Economics*, 22(3), 235-246.
- Li, X., Gan, C., & Hu, B. (2011b). The welfare impact of microcredit on rural households in China. *The Journal of Socio-Economics*, 40(4), 404–11.
- Long, J. S., & Freese, J. (2014). *Regression Models for Categorical Dependent Variables Using Stata*. Texas: A Stata Press Publication.
- Luxchaigul, N. (2014). The effective of sustainable development of the saving for production groups in northeast of Thailand. *Environment Management and Sustainable Development*, 3(1), 168-180.
- Maddala, G. S. (1994). *Limited-dependent and Qualitative Variables in Econometrics* (reprinted Ed.). New York, USA: Cambridge University Press.
- Maes, J., & Foose, L. (2006) *Microfinance services for very poor people: promising approaches from the field*. Paper commissioned by the 2006 Annual Microcredit Summit Campaign. Available at http://www.microcreditsummit.org/commissioned_papers/
- Mahapatra, M. S., & Dutta, S. (2016). Determinants of sustainability of microfinance sector in India. *Journal of Rural Development*, 35(3), 507-522.
- Marr, A. (2012, October). Effectiveness of rural microfinance: What we know and what we need to know. *Journal of Agrarian Change*, 12(4), 555-563.
- McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontier of Economics*, 105-142. New York: Academic Press
- Meagher, P. (2013). *Microfinance regulation and supervision recommendations report*. Asian Development Bank.
- Menkhoff, L., & Rungruxsirivorn, O. (2011). Do village funds improve access to finance? Evidence from Thailand. *World Development*, 39(1), 110-122. doi:10.1016/j.worlddev.2010.09.002
- Mersland, R. & Strøm, R. Ø., (2009). Performance and governance in microfinance institutions. *Journal of Banking & Finance*, 33(4).
- Meyer, J. (2019). Outreach and performance of microfinance institutions: the importance of portfolio yield. *Applied Economics*, 51(27), 2945-2962.
- Meyer, R. L. (2002). *Track record of financial institutions in assisting the poor in Asia*. ADB research Institute Paper, No. 49.

- Microfinance Services Ltd. (2013). *Thailand financial inclusion synthesis assessment report*. Kingdom of Thailand: Development of a strategic framework for financial inclusion. Asian Development Bank. Retrieved from <https://www.adb.org/sites/default/files/project-document/81802/45128-001-tacr-01-0.pdf>
- Mishkin, F. S. (2004). *The Economics of Money, Banking and Financial Market* (7th ed.). Boston, USA: Pearson Addison-Wesley.
- Mohamed, K. (2003). *Access to formal and quasi-formal credit by smallholder farmers and artisanal fishermen: a case of Zanzibar*. Research Report No. 03.6, Dares Salaam, Tanzania: Research on Poverty Alleviation (REPOA).
- Mokhtar, S. H. (2011). *Microfinance performance in Malaysia*. Unpublished doctoral thesis. Lincoln University, Lincoln, New Zealand.
- Montgomery, H. (2005). *Meeting the double bottom line – The impact of Khushhali bank's microfinance program in Pakistan*. Tokyo: ADBI.
- Morduch, J. (1998). *Does microfinance really help the poor? New evidence from flagship programs in Bangladesh*. Working paper no. 21, Research Program in Development Studies, Princeton University.
- Mosley, P. & Rock, J. (2004). Microfinance, labour markets and poverty in Africa: A study of six institutions. *Journal of International Development*, 16(3), 467-500.
- Mpuga, P. (2008). *Constraints in access to and demand for rural credit: Evidence from Uganda*. A paper for presentation during the African Economic Conference (AEC), 12-14 November 2008, Tunis, Tunisia.
- Muriu, P. (2011). *Microfinance Profitability: What explains the low profitability of African microfinances?* (Unpublished doctoral thesis). Birmingham Business School, University of Birmingham, Birmingham, England.
- Navajas, S., Schreiner, M., Meyer, R. L., Gonzalez-vega, C., & Rodriguezmeza, J. (2000). Microcredit and the poorest of the poor: theory and evidence from Bolivia, *World Development*, 28, 333–46. doi:10.1016/S0305-750X(99)00121-7
- Ngo, T. V. (2012). *Capital structure and microfinance performance: A cross-country analysis and case study of Vietnam*. (Unpublished doctoral thesis). University of Birmingham, Birmingham, England.
- Nguyen, C. H. (2007). *Determinants of credit participation and its impact on households consumption: evidence from rural Vietnam*. Edinburgh: Centre for Economic Reform and Transformation, Heriot Watt University. Retrieved from <http://ideas.repec.org/p/hwe/certdp/0703.html>
- Nyamsogoro, G. D. (2010). *Financial sustainability of rural microfinance institutions in Tanzania*. (Unpublished doctoral thesis). The University of Greenwich, Greenwich, England.
- Office of the National Economic and Social Development Board [NESDB]. (2015). Poverty data. Retrieved from <http://www.nesdb.go.th>
- Office of the National Economic and Social Development Board [NESDB]. (2017). *The twelfth national economic and social development plan (NESDP)*. Retrieved from https://www.nesdb.go.th/nesdb_en/ewt_w3c/ewt_dl_link.php?nid=4345
- Okurut, F. N. (2006). *Access to credit by the poor in South Africa: evidence from household survey data 1995 and 2000* (Working Papers 13/06). University of Stellenbosch, Department of Economics and the Bureau for Economic Research.

- Osborne, J. W., & Waters, E. (2002). Four assumptions of multiple regression that researchers should always test. *Practical Assessment, Research & Evaluation*, 8(2), 1-5.
- Petrick, M. (2005). Empirical measurement of credit rationing in agriculture: A methodological survey. *Agricultural Economics*, 33(2), 191-203.
- Pham, B. D., & Izumida, Y. (2002). Rural development finance in Vietnam: A microeconomic analysis of household surveys. *World Development*, 30(2), 319-335.
- Pham, T. T. T., & Lensink, R. (2007). Lending policies of informal, formal and semiformal lenders evidence from Vietnam. *Economics of Transition*, 15(2), 181-209.
- Phan, D. K. (2012). *An empirical analysis of accessibility and impact of microcredit: The rural credit market in the Mekong River Delta, Vietnam*. (Unpublished doctoral thesis). Lincoln University, Lincoln, New Zealand.
- Phan, D. K., Gan, C., Nartea, G. V. & Cohen, D. A. (2013), *Impact of microcredit on rural households: An evaluation using panel data*. Faculty of Commerce Working Paper no. 7, Lincoln University.
- Pitt, M. M., & Khandker, S. R. (1998). The impact of group-based credit programs on poor households in Bangladesh: Does the gender of participants matter? *Journal of Political Economy*, 105(5), 958-996.
- Popova-Nowak, I. V., & Cseh, M. (2015). The meaning of organizational learning: A meta-paradigm perspective. *Human Resource Development Review*, 14(3), 299-331. DOI: 10.1177/1534484315596856
- Quach, M. H. (2005). *Access to finance and poverty reduction: an application to rural Vietnam*. (Unpublished doctoral thesis). University of Birmingham, Birmingham, England.
- Quayes, S. (2012). Depth of outreach and sustainability of microfinance institutions. *Applied Economics*, 44, 3421-3433.
- Quayes, S. (2015). Outreach and performance of microfinance institutions: a panel analysis. *Applied Economics*, 47(18), 1909-1925. doi: 10.1080/00036846.2014.1002891
- Rahman, M. A., & Mazlan, A. R. (2014). Determinants of financial sustainability of microfinance institutions in Bangladesh. *International Journal of Economics and Finance*; 6(9), 107-116.
- Robinson, M. S. (2001). *The Microfinance Revolution: Sustainable Finance for the Poor*. Washington, D.C.: The International Bank for Reconstruction and Development/The World Bank.
- Romer, D. (2001). *Advanced Macroeconomics* (2nd Ed.). New York, U.S.A.: McGraw-Hill.
- Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55.
- Rosenberg, R. (2009). Measuring results of microfinance institutions: Minimum indicators that donors and investors should track. *Consultative Group to Assist the Poor, The World Bank*.
- Ruiz-Tagle, J. (2005). *Borrowing in developing countries: who can access credit and at what cost?* Unpublished paper. Retrieved from <http://www.econ.cam.ac.uk/phd/jr280/>
- Santoso, D. B. (2016). *Credit accessibility: the impact of microfinance on rural Indonesian households*. (Unpublished Master's thesis). Lincoln University, Lincoln, New Zealand.

- Saqib, S. E., Ahmad, M. M., Panezai, S., & Ali, U. (2016). Factors influencing farmers' adoption of agricultural credit as a risk management strategy: The case of Pakistan. *International Journal of Disaster Risk Reduction*, 17, 67-76.
- Sarap, K., (1990). Factors affecting small farmers' access to institutional credit in rural Orissa, India. *Development and Change*, 21 (2), 281-307.
- Schäfer, K., & Fukasawa, Y. (2011). Factors determining the operational self-sufficiency among microfinance institutions. *Advances in Business Research*, 2(1), 172-178.
- Schreiner, M. (1996). *Thinking about the performance and sustainability of microfinance organizations*. Retrieved from http://www.microfinance.com/English/Papers/Thinking_about_Sustainability.pdf
- Schreiner, M. (2000). Ways donors can help the evolution of sustainable microfinance organizations. *Savings and Development*, 24, 423-37.
- Schreiner, M. (2003). *Subsidies and subsidized funds*. In *The Performance of Subsidized Microfinance Organizations: BancoSol of Bolivia and the Grameen Bank of Bangladesh*. Lewiston, New York: The Edwin Mellen Press, Ltd.
- Sebatta, C., Wamulume, M., & Mwansakilwa, C. (2014). Determinants of smallholder farmers' access to agricultural finance in Zambia. *Journal of Agricultural Science*, 6(11), 63-73.
- Sekabira, H. (2013). Capital structure and its role on performance of microfinance institutions: The Ugandan case. *Sustainable Agriculture Research*, 2(3), 86-100.
- Setboonsarng, S., & Parpiev, Z. (2008). Microfinance and the millennium development goals in Pakistan: Impact assessment using propensity score matching. *ADB Institute*, Discussion paper no. 104.
- Shahzad, U. B. (2015). *Performance measurement of South Asian microfinance institutions*. (Unpublished doctoral thesis). Massey University, Palmerston North, New Zealand.
- Shaoyan, S., & Duwal, B. R. (2012). Comparative analysis of financial sustainability of Nepalese microfinance institutions. *International Journal of Business Management, Economics and Information Technology*. 4(2), 233-241.
- Siamwalla, A., Pinthong, C., Poapongsakorn, N., Satsanguan, P., Nettayarak, P., Mingmaneeakin, W., & Tubpun, Y. (1990). The Thai rural credit system: Public subsidies, private information, and segmented markets. *The World Bank Economic Review*. 4(3), 271-295.
- Sima, G. (2013). Determinants of profitability: An empirical study on Ethiopian microfinance institution. (Unpublished Master's thesis). Addis Ababa University, Addis Ababa, Ethiopia.
- Smith, J., & Todd, P. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125(1-2), 305-353.
- Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review*, 71(3), 393-410.
- Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science : A Review Journal of the Institute of Mathematical Statistics*, 25(1), 1–21. <http://doi.org/10.1214/09-STS313>
- Swain, R. B., & Floro M. (2012). Assessing the effect of microfinance on vulnerability and poverty among low income households. *The Journal of Development Studies*, 48(5), 605-618. doi: 10.1080/00220388.2011.615917

- Takahashi, K., Higashikata, T., & Tsukada, K. (2010). The short-term poverty impact of small-scale, collateral-free microcredit in Indonesia: A matching estimator approach. *The Developing Economies*, 48(1), 128–55.
- Tambunlertchai, K. (2015). Financial inclusion, financial regulation, and financial education in Thailand. ADBI Working Paper 537. Tokyo: Asian Development Bank Institute. Retrieved from <http://www.adb.org/publications/financial-inclusion-financial-regulation-financial-education-thailand/>
- Tang, S., Guang, Z., & Jin, S. (2010). Formal and informal credit markets and rural credit demand in China. *Paper selected for presentation at the Agricultural and Applied Economics Association*. Denver, Colorado, July 25-27, 2010
- Tarozzi, A., Desai, J., & Johnson, K. (2015). The impacts of microcredit: evidence from Ethiopia. *American Economic Journal: Applied Economics*, 7(1), 54–89.
- Tehulu, T. A. (2013). Determinants of financial sustainability of microfinance institutions in East Africa. *European Journal of Business and Management*, 15(7), 152-159.
- Thailand Development Research Institution [TDRI]. (2004). *Micro-banking development*. Retrieved from <http://www.info.tdri.or.th>
- The World Bank. (2019a). *Thailand economic monitor, inequality, opportunity and human capital*. Retrieved from <http://documents.worldbank.org/B225887A-6DB2-4029-BBBA-8A5476CE112C/FinalDownload/DownloadId-2D0A18FC50FA9A31078601AD23034AFA/B225887A-6DB2-4029-BBBA-8A5476CE112C/curated/en/154541547736805518/pdf/133835-REVISED-2-Thailand-Economic-Monitor-Jan-2019-FINAL.pdf>
- The World Bank. (2019b). World Bank open data. Retrieved from <https://data.worldbank.org/>
- Turnovsky, S., & García-Peñalosa, C. (2008). Distributional dynamics in a neoclassic growth model: the role of elastic labor supply. *Journal of Economic Dynamics & Control*, 32, 1399-1431.
- Umoh, G. S. (2006). Empirical investigation of access to micro-credit in an emerging economy: evidence from Nigeria. *Journal of African Business*, 7 (1/2), 89-117.
- Verbeek, M. (2008). *A Guide to Modern Econometrics* (3rd Ed.). Sussex, England: John Wiley & Sons Ltd.
- Wachira, M. I., & Kihui, E. N. (2012). Impact of financial literacy on access to financial services in Kenya. *International Journal of Business and Social Science*, 3(19), 42-50.
- Waelde, H. (2011). Demasking the impact of microfinance. *Gutenberg School of Management and Economics Discussion Paper No. 1115*. Mainz: Gutenberg School of Management and Economics.
- Warr, P. (2000). Is growth good for the poor? Thailand's boom and bust. *International Journal of Social Economics*, 27 (7-10), 862-877. Retrieved from <http://econ.tu.ac.th/class/archan/Rangsun/EC%20460/EC%20460%20Readings/Thai%20Economy/Is%20Growth%20Good%20for%20the%20Poor.pdf>
- Warr, P. (2011). Thailand's development strategy and growth performance. Working paper, *World Institute for Development Economics Research*. ISBN 978-92-9230-365-5
- Wassie, S. B., Kusakari, H., & Sumimoto, M. (2019). Performance of microfinance institutions in Ethiopia: Integrating financial and social metrics. *Social Science*, 8(117), 1-13.
- White, H., & Sabarwal, S. (2014). *Quasi-experimental design and methods*. Methodological briefs: impact evaluation no.8, UNICEF Office of Research, Florence.

- Williams, R. (2018). Post-estimation commands for mlogit. *Stata Journal*, 1–10.
- Woldeyes, M. T. (2012). *Determinants of operational and financial self-sufficiency: An empirical evidence of Ethiopian microfinance institutions*. (Unpublished Master's thesis). Addis Ababa University, Addis Ababa, Ethiopia.
- Woller, G. & Parsons, R. (2002). Assessing the community economic impact of microfinance institutions. *Journal of Developmental Entrepreneurship*, 7(2), 133-150.
- Wooldridge, J. M. (2007). *Econometric analysis of cross section and panel data*. Cambridge: MAMIT Press.
- Wooldridge, J. M. (2009). *Introductory economics: A modern approach* (4th Ed.). Mason, U.S.A.: South-Western.
- Yenesew, A. (2014). *Determinants of financial performance: A study on selected micro finance institutions in Ethiopia*. (Unpublished Master's thesis). Jimma University, Ethiopia.
- Yostrakul, W. (2018). *One size does not fit all: A case study of microfinance impact in rural Thailand*. Unpublished doctoral thesis, University of Leicester, Leicester, England.
- Zeller, M. (1994). Determinants of credit rationing: A study of informal lenders and formal credit groups in Madagascar. *World Development*, 22(12), 1895-1907.
- Zeller, M., & Meyer, R. (2002). *The Triangle of Microfinance*. Baltimore: The John Hopkins University Press.